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Improvement and Replacement: The Dual Impact of Automation on Employees' Job Satisfaction

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Abstract: Research focuses mainly on the impact of automation on employment and wages but pays little attention to its impact on employee job satisfaction, especially in the context of the Global South. Using survey data from China, this article investigates the impact of automation on employee job satisfaction due to the effects of job improvement and position replacement stress. The results indicate that automation can improve the job satisfaction of individual employees but reduces the job satisfaction of employees with a position that can be replaced easily by automation. The improvement and replacement effects coexist within the impact of automation. Through a structural equation model, this article finds that the improvement effect arises from an increase in job income, safety, and ability, whereas replacement stress is produced through the mediating effect of job stress and boredom. The heterogeneity analysis shows that the improvement effect is present in young employees with low job skills, position competency, and experience requirements, while replacement stress occurs in middle-aged and elderly employees with high job skills and high position competency and experience requirements. Our study provides evidence for the construction of an internal labor market in enterprises and labor policy interventions in the digital age.

Keywords: automation; job satisfaction; China; enterprise employees

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1. Introduction

Automation technologies have significantly affected industry development, which is believed to lead to a new industrial revolution [1]. Current research on automation focuses mainly on its impact on economic development, industrial advancement, management, wages, and employment [2–5], but pays little attention to the feelings of individual employees, such as job satisfaction or wellbeing. The ultimate goal of technological development is to not only promote economic growth and industrial progress, but also improve employees' social wellbeing and provide people with an increased sense of security, happiness, and satisfaction.

Within existing studies on automation and labor outcomes, there are ongoing debates on the impacts of automation on employee job satisfaction. On the one hand, some studies showed that the adoption of automation can contribute to industrial and social upgrading, including working conditions, labor rights, and job security [6–8], which may positively improve employees' wellbeing and job satisfaction [9]. On the other hand, the implementation of automation may reduce employees' job autonomy and increase their work intensity, such as intensifying work rhythms and labor effort, thereby further disengaging and distancing them from their work, which can negatively impact job satisfaction [10–12]. The former idea holds an optimistic opinion about automation and job satisfaction and treats automation as a critical factor in improving industrial productivity and employees' job satisfaction. However, the latter argument is highly concerned about the negative impact of automation, which may replace employees and result in "technological unemployment" [2], thereby leading to reduced job satisfaction.

In this study, we aim to provide new empirical findings for this debate. Based on the debate above, we find that the effects of automation may coexist in the labor process but have different impacts on different levels. Therefore, we propose that the impact of automation on employees' job satisfaction can be explained on two levels. On an individual level, the use of automation can enable employees to be highly productive, improve their working conditions, and enhance their work quality. As a result, employees may gain increased leisure time, opportunities, and security, which may lead to increased satisfaction with their work. At the position level, the higher the degree of automation adoption in a given position, the greater the risk and stress of employees in positions to be replaced. Automation may reshape the work processes, labor intensity, management rules, and job prospects of such positions, thereby affecting employees' psychological perceptions and expectations. Therefore, current research may have overlooked the differences between individual employees and their job positions when examining the impact of automation, thereby generating divergences in explaining employees' attitudes toward automation.

Job satisfaction is one of the most important psychological wellbeing factors for enterprise employees [13,14]. Unsatisfied employees typically have little motivation to work hard and high turnover intentions, which in turn will affect productivity and innovation in the economy [15]. Current research indicates that employee job satisfaction is mainly affected by two categories of factors: individual characteristics and work–organizational conditions. Individual characteristics include gender, age, education, health, and skills [13,16,17]. Work–organizational conditions involve salary, job security, work pressure, work autonomy, and the working environment [12,14,18,19]. However, there is a limited body of research exploring changes in employee psychological wellbeing in the context of technological advancements, particularly concerning emerging trends such as automation. Therefore, using data from the 2018 China Labor-force Dynamics Survey (CLDS), which is a national workforce survey in China, we investigate the impact of automation on employee job satisfaction at the individual and position levels and explore the underlying factors of this impact and the manifestation of heterogeneity among employees.

The use of automation is increasing at breakneck speed around the world, especially in China. According to a report from World Robotics, in 2021, an all-time high of 517,385 new industrial robots were installed in factories worldwide, with those in China accounting for 51%, with 268,195 units shipped [20], thereby indicating the rapid speed of robotization and automation in the country. Moreover, China has become the world's largest market for industrial robots. The development of automation in China can be attributed to government policies such as the Made in China 2025 program of the Ministry of Industry and Information Technology, which provides substantial subsidies to enterprises to upgrade the industry, ranging from being labor-intensive to being technology-intensive (with the slogan "Replacing Humans with Machines"), and face the challenges of the declining labor force, rising wages, and ensuing skill bottlenecks eroding China's international competitiveness. However, because of the weak power of labor unions [7], employees have little bargaining power in the decision to adopt automation; thus, understanding their psychological perception of the postadoption of automation and its effect on job satisfaction is difficult. In addition, stress from automation pushes young employees to move from the manufacturing industry to the platform economy [21–23]. By analyzing the impact of automation on employees in China, our study contributes to understanding the changes in employees' psychological perceptions under the digital wave and provides evidence for the construction of labor policies.

2. Theory and Hypotheses

2.1. Improvement Effect of Automation

Although debates on the impact of automation on work, employment, and wages abound, the common perception is that automation technologies have the advantages of high efficiency, convenience, and the ability to perform job tasks beyond the reach of manpower. Such advantages can not only promote industrial and enterprise productivity but also lead to high income for employees and improved working environments, work safety, and performance, which can contribute to a high level of job satisfaction [14,24]. In the succeeding section, we identify the improvement effects of automation on job satisfaction from three aspects.

First, automation can increase enterprise efficiency and productivity, thereby improving employees' income and job stability. Studies revealed that enterprises undergoing automation transformation and upgrading can reduce costs and improve enterprise productivity [25,26]. Improvements in enterprise productivity will in turn lead to an increase in the labor income share. As a result, with the increased use of automation in the manufacturing sector, such as industrial robots, wages and the skill premium will increase [3,27,28]. Besides labor efficiency and benefits, automation demands high enterprise capabilities, such as quality and management efficiency, and can reduce the uncertainty risk of enterprise operations to a considerable extent [29], which can contribute to the improvement of employees' job stability in the workplace.

Second, automation can improve employees' working environment, health, and safety. Work safety and environmental risk are important factors influencing job satisfaction [30]. Typically, the more intense the work and the higher the work environment risk, the lower the job satisfaction of employees [12]. According to a survey in the United States, each standard deviation increase in the use of robots can reduce workplace injuries by about 16%. Moreover, in Germany, scholars found that automation reduces the physical intensity of work by 4% and the risk of disability by 5% [31]. Improved working environments and decreased physical work can improve employees' health. Gunadi and Ryu [32] found that the rise in automatic and robotic technology is positively related to the health of employees, especially low-skilled workers. In addition, a 10% increase in robotics use for every 1000 employees reduces the proportion of low-skilled employees reporting poor health by approximately 10%. Enterprises' implementation of automation can also effectively improve the quality of employees' working conditions and working environment, thereby leading to increased job satisfaction [14,33].

Finally, automation can improve employees' abilities or "sense of competence" at work, which is another important source of job satisfaction [34]. Automation increases productivity but also necessitates high skills from employees. Employees can also improve their job skills and knowledge acquisition as they adapt to technological advancements [35]. In addition, technologies such as automation have changed job designs and increased gamification in the working process, which are conducive to increasing employees' motivation, satisfaction, and performance [36]. In all, at the individual level, automation increases job satisfaction through the improvement of individual efficiency, welfare, and competence. Considering the discussion above, we propose the following hypothesis:

Hypothesis 1. *Employees affected by the use of automation have a high level of job satisfaction.*

2.2. Replacement Stress from Automation

Although automation may have positive effects, debates abound on the impact of automation on job satisfaction, involving two main effects of automation on employment. The first pertains to the replacement stress engendered by automation. Studies have emphasized that various types of automation can replace human labor for numerous manual tasks, thereby leading to employees' concerns about job loss and technological unemployment [2,37,38]. Some empirical findings indicated that the adoption of automation has replaced certain workers, and employees working with automation and smart machines expressed worry and concern about being replaced by automation in the future [16,39], which can negatively affect their job satisfaction. Second, in contrast with the fear of automation, the theory of the "compensation and creation effect" [9] states that the development of automation can stimulate positive spillover effects and catalyze the production of new labor demand in the market, which can create new jobs [4].

The reasons for the debates on the replacement effect of automation may derive from employees' analytical levels. In other words, automation has differentiated effects on different types of employees. Research has indicated that employees in a low position and who perform repetitive work with low skills are highly likely to be replaced [3,16], whereas the use of automation is linked with an increase in aggregate employment [4]. Thus, analyzing these heterogeneous effects and understanding their underlying mechanisms are crucial.

The increasing use of automation in specific industries and occupations has induced "invisible stress" for employees, which is the opposite of the improvement effect. Work condition surveys also observed the replacement effect in several European countries and in the United States. According to the European Working Conditions Survey, "robotization" has a negative impact on the quality of work, which makes employees' tasks highly dependent on the pace of work of machines [10]. In Norway, the recent trend of enterprise automation led to concerns among 40% of employees about their job being replaced by smart machines, which had a negative impact on their job satisfaction [16]. In Germany, a study showed that for every twofold increase in robot adoption in the rapid automation industry, employees' mental health decreased by 1.18 standard deviation, and the degree of automation will likely affect the mental health of young employees [40]. Analyzing data from multinational job status surveys, Gorny and Woodard [13] found that each standard deviation increase in automation led to a decrease in job satisfaction of approximately 0.64% to 2.61%.

Studies have revealed that both effects exist simultaneously in China's labor market. On the one hand, forms of automation such as industrial intelligence and robotics exert a major "replacement effect" on the manufacturing industry, gradually pushing some employees out [7,8]. A study highlighted that a 1% increase in the adoption of industrial robots is associated with a 4.6% reduction in the number of jobs [41]. Therefore, the adoption of automation can decrease the occupational mobility intentions of young employees with low socioeconomic status and low levels of occupational specialization [42]. On the other hand, automation can promote the inflow and development of human capital in the service industry, thereby inducing the emergence of a new trend of middle-educated and low-skilled labor moving to the service industry and "platform economy" [23]. Overall, the labor market in China is espousing the trend of "Replacing Humans with Machines" [8].

Based on existing findings, our empirical research presents two contrasting outcomes regarding automation's impact: the use of automation appears to both "increase" and "decrease" employees' job satisfaction. Discussions on both findings ignore the differences in the impact of automation on individuals and positions. Although automation can improve employees' working conditions, they may experience technological replacement stress from the industry and their positions. Thus, certain positions induce structural replacement stress from automation, which creates a negative effect on job satisfaction. Based on this consideration, we propose the following hypothesis:

Hypothesis 2. *Employees in a position with a high automation replacement rate have a low level of job satisfaction.*

3. Data, Variables, and Methods

3.1. Data

We used data from the 2018 China Labor-force Dynamics Survey (CLDS), which is a nationally representative survey of China's labor force. The China Labor-force Dynamics Survey (CLDS), conducted by the Social Science Survey Center at Sun Yat-sen University, involves biennial dynamic tracking surveys of families and individual labor force members in urban and rural areas of China, with villages/neighborhoods as the tracking units. The survey covers 29 provinces and cities in China, with a valid sample size of 16,538. The survey subjects are the entire labor force in the household sample. According to the purpose of our study, we used the sample of enterprise employees from the survey data, with a valid sample size of 3088 individuals.

3.2. Variable Description

The dependent variable was job satisfaction, which we measured with the following question: "Overall, how satisfied are you with your current job?" The responses were scored based on a scale ranging from 1 (very unsatisfied) to 5 (very satisfied). Prior research indicated that this single item demonstrates satisfactory reliability and validity in measuring job satisfaction [13,16,39].

The key independent variable was the impact of automation on enterprise employees. We measured it from two aspects. (1) The first aspect was the individual level of the effect of automation. Measuring the exact impact of automation poses a challenge, but measuring the perceived changes in intensity resulting from automation adoption is feasible. Therefore, the effect of automation was measured by the respondents indicating whether their current job was changed by automation technologies such as automation, robotics, or AI. We coded the affected and unaffected respondents as 1 and 0, respectively. Among the participants, 6.25% responded that their job was affected. (2) The second aspect was the position replacement rate by automation. The risk of the replacement effect of automation in different positions reflects the role of automation technologies in reconstructing job content and indicates the position aggregation effect of automation adoption. Drawing on the research of Frey and Osborne [43], Yao et al. [44] calculated the replacement rate of 61 occupations and 19 industries from the Chinese Classification Standards for Occupations and Industries. The two indicators reflected the current automation trend in China and the risk of jobs being replaced by automation technologies in the next 20 years. As the work content of the same occupations in different industries is diversified [29], in this study, we coded the respondents' occupational and industrial replacement rates from automation as the "replacement rate of occupation" (RRO) and the "replacement rate of industry" (RRI). Next, we multiplied the two replacement rate measures to obtain the "replacement rate of position" (RRP) variable (RRP = RRI $\times$ RRO).

We obtained 353 positions from the data sample, with the highest replacement rate of 25.7% for the "occupations of production, assembly and maintenance in the manufacturing industry" and the lowest of 0.002% for the "nursing occupations in health, sports, and social welfare industries". The average replacement rate of the sample was 8.5%, with a standard deviation of 6.4%.

We adjusted the following demographic variables as the control variables in the estimation model: gender (53.5% male and 46.5% female); age, with a mean value of 40.3 years and standard deviation of 11.5; educational level according to the Chinese educational system, in which we converted the educational levels in the survey into years of education (mean value of 11.6 and standard deviation of 3.7); and marital status (81.5% married and 18.5% unmarried). We measured wages with the respondents' before-tax wage income in 2017, which we analyzed by taking the natural logarithm, with a mean of 10.6 and a standard deviation of 0.9. We also measured whether a participant was a contractual employee (59.5% of the employees were contractual, and 40.5% were not contractual) and whether job training was provided (55.2% of the employees were trained, and 49.8% were not trained). For physical labor intensity, we converted the answers to the question "Does the job require heavy physical labor?". We coded "often" as "high intensity" and "sometimes", "rarely", and "never" as "low intensity". For the answers, 33.4% were high intensity, and 66.6% were low intensity. Table 1 presents descriptive statistics for this study.

Table 1. Descriptive statistics.

	Mean	SD	Min	Max
Dependent variable				
Job satisfaction	3.569	0.708	1	5
Independent variables				
Affected by automation	0.063	0.242	0	1
RRP	0.085	0.065	0.00002	0.257
Control variables				
Gender	0.535	0.499	0	1
Age	40.337	11.458	15	79
Age Squared/100	17.583	9.595	2.25	62.41
Marital status	0.815	0.389	0	1
Years of education	11.597	3.730	0	19
Wage (logged)	10.583	0.893	1.609	13.816
Weekly working hours	47.226	18.234	0	168
Contractual	0.595	0.491	0	1
Trained	0.552	0.497	0	1
Physical labor intensity	0.334	0.472	0	1

3.3. Statistical Model

As the variable structure of this study contained explanatory variables at the individual employee level and automation replacement rate variables at the job level, we used a multilevel linear model to estimate the data. The following equations represent the research model:

$$\text{Individual level: } JS = \beta_{0j} + \beta_{1j} \cdot IIA + \beta_{mj} \cdot CV + \varepsilon_{ij}, \tag{1}$$

$$\text{Job level: } \beta_{0j} = \gamma_{00} + \gamma_{01} \cdot RRP + u_{0j}, \tag{2}$$

The overall estimating equation is

$$JS = \gamma_{00} + \beta_{1j} \cdot IIA + \gamma_{01} \cdot RRP + \beta_{mj} \cdot CV + \varepsilon_{ij} + u_{0j}, \tag{3}$$

where JS is job satisfaction; IIA is the impact of automation on an individual employee; RRP is the replacement rate of a position by automation; CV is the control variables of the model; β_{1j}, γ_{01}, and β_{mj} are the regression coefficients; ε_{ij} is the individual-level residual; and u_{0j} is the job-level residual.

4. Results

4.1. Impact of Automation on Employees' Job Satisfaction

Table 2 shows the results of the multilevel linear model analysis of job satisfaction, in which Model 3 is the target model of our study. For comparison, we include the replacement rate by automation for the industry and occupation in Model 1 and Model 2, respectively. Based on the three models, within individual characteristics, job satisfaction is higher among female employees. Age exhibits a U-shaped relationship with job satisfaction, initially decreasing and then increasing. Regarding work and enterprise characteristics, higher wages, shorter working hours, participation in enterprise training, and lower physical labor intensity are associated with increased job satisfaction, However, our main focus is on exploring the impact of automation at the individual and job levels. In all three models, employees affected by automation report a high level of job satisfaction, which supports Hypothesis 1. By contrast, at the job level, the effect of the replacement rate by automation is not significant at the industry level and negatively significant at the occupation and position levels. This finding supports Hypothesis 2, stating that employees in a position vulnerable to being replaced by automation will have low job satisfaction. This result also suggests that compared with broader industries, the adoption of automation based on specific work contents and positions plays a more significant role in employees' psychological wellbeing.

Table 2. Impact of automation on job satisfaction.

	Model 1		Model 2		Model 3	
Individual level						
Male	−0.074 **	(0.027)	−0.074 **	(0.027)	−0.077 **	(0.027)
Age	−0.032 ***	(0.008)	−0.032 ***	(0.008)	−0.032 ***	(0.008)
Age squared/100	0.004 ***	(0.000)	0.004 ***	(0.000)	0.004 ***	(0.000)
Marital status	0.015	(0.039)	0.015	(0.039)	0.014	(0.039)
Years of education	0.001	(0.004)	−0.001	(0.004)	−0.000	(0.004)
Wage (logged)	0.046 **	(0.016)	0.042 **	(0.016)	0.044 **	(0.016)
Weekly working hours	−0.002 *	(0.001)	−0.002 *	(0.001)	−0.002*	(0.001)
Contractual	0.040	(0.029)	0.036	(0.029)	0.038	(0.029)
Trained	0.071 *	(0.029)	0.064 *	(0.029)	0.066 *	(0.029)
Physical labor intensity	−0.198 ***	(0.028)	−0.190 ***	(0.028)	−0.192 ***	(0.028)
Affected by automation	0.129 *	(0.052)	0.120 *	(0.052)	0.129 *	(0.052)
Job level						
RRI	−0.209	(0.157)				
RRO			−0.243 *	(0.111)		
RRP					−0.556 *	(0.246)
Constant	3.762 ***	(0.214)	3.831 ***	(0.215)	3.784 ***	(0.212)
Number of groups	17		61		353	
Observations	3088		3088		3088	
Intraclass correlation coefficient	4.9%		2.2%		1.1%	

Note: * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$; standard errors are in parentheses; RRI refers to replacement rate of industry, RRO refers to replacement rate of occupation, and RRP refers to replacement rate of position.

4.2. Robustness Checks

The model results exhibit potential robustness issues. First, employees who are dissatisfied with their job owing to the impact of automation may also choose to leave their vulnerable position, which may create a self-selection-based endogeneity bias [45]. To address this issue, we use preference for the introduction of automation (i.e., "not introduced", "introduced", and "introduced and ready for further introduction") in the employees' enterprise as the instrumental variables to conduct the model estimation. According to previous studies, the decision to introduce, implement, or upgrade automation is typically made by managers rather than by employees [11,46]. Therefore, the higher the tendency of an enterprise to introduce automation, the more likely the individual employee or his/her position to be influenced by the automation, while individual employees' job satisfaction is less likely to be influenced by the enterprise's technology preference. As the endogenous variable "whether or not influenced by automation" is a binary variable, we use the conditional mixed process (CMP) approach to estimate the instrumental variable [47].

Table 3 shows the robustness test results. The first-stage result shows that, besides the significant effect of the instrumental variables, namely, the automation preference of enterprises, male employees and physical labor employees are more easily impacted by automation. According to the results of the conditional mixed model, atanhrho_12 reflects the residual correlation of the two-stage regression model, which is significant at the 95% confidence interval, thereby indicating that the model is endogenous, and the conditional mixed-model estimation results are better than those of the multiple regression model. Based on the estimation of the instrumental variable-based CMP approach and after excluding the endogenous effects, we can see that the results of the regression analysis are consistent with the coefficients and significance of the regression results in Table 2. Therefore, the findings of this study are robust.

Table 3. Robustness tests.

	Stage 1: Affected by Automation		Stage 2: Job Satisfaction	
Male	0.241 *	(0.120)	−0.086 **	(0.026)
Age	−0.015	(0.037)	−0.032 ***	(0.008)
Age squared/100	0.014	(0.044)	0.045 ***	(0.009)
Marital status	−0.125	(0.167)	0.017	(0.039)
Years of education	0.007	(0.019)	0.003	(0.004)
Wage (logged)	−0.019	(0.059)	0.041 **	(0.016)
Weekly working hours	0.001	(0.003)	−0.002 *	(0.001)
Contractual	−0.193	(0.140)	0.028	(0.029)
Trained	0.087	(0.138)	0.077 **	(0.029)
Physical labor intensity	0.262 *	(0.122)	−0.195 ***	(0.028)
Affected by automation			0.073 *	(0.033)
RRP			−0.604 **	(0.213)
Automation preference of enterprises	1.587 **	(0.077)		
Constant	−2.320 ***	0.893	3.788 ***	0.211
atanhrho_12			0.781 ***	(0.080)

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; standard errors are in parentheses.

4.3. Mediating Effect of Impact of Automation

Compared with the advantages brought about by automation, such as efficiency and safety, the mechanism of replacement stress on individual job satisfaction is relatively obscure. Understanding the specific pathways of the structural effects of technological development on employees' psychological perceptions and intermediate mechanisms enhancing employees' job satisfaction would be helpful.

Based on the literature, we propose that automation replacement stress can affect employees' job satisfaction through two pathways. The first pathway is the work stress path. In contrast to the arguments about automation technologies such as automation increasing labor efficiency, thereby providing increased leisure time, the relevant case studies suggest that employees in a position with a high level of technology adoption may experience stronger work stress. Automation, represented by robotics and algorithms, controls the rhythm of work, and employees will likely keep up with the pace of technology instead of having labor autonomy. This observation means that physical and mental stress from work is elevated because of the dominance of technology, thereby reducing job satisfaction [10,48,49]. The second path is boredom from work. While automation may display the increasing complexity of jobs, it may decrease employees' level of autonomy [11]. Simply monitoring screens, such as controlling and operating certain machines and programs, can create a sense of monotony. A study found that technological replacement pressure results not from employees' fear of losing their job but rather from the monotony and low self-perceived meaning of work, which can lead to low satisfaction [13,50]. In addition, digital traceability mechanisms and algorithmic control can create labor alienation [22], which can have a demotivating effect on the joy and meaning of work. The two paths differ from the immediate impact of job replacement stress; rather, they indicate that the high degree of automation adoption in easily replaceable positions can reconstruct work contents and processes, thereby affecting employees' perception of job satisfaction.

Therefore, we use two Likert scale questions, that is, "I feel physically and mentally exhausted at work" and "I have become increasingly uninterested in my work", to act as a proxy to measure job stress and boredom. In addition, as previously mentioned, the improvement effect of automation on job satisfaction can be influenced by factors such as income, safety, and a sense of ability. Therefore, we included satisfaction among these three categories of working conditions as mediating variables to evaluate the respondents' job satisfaction at the individual level.

Based on the mechanism of the mediating effect mentioned above, we determine that employees in jobs with a high replacement rate by automation will likely be affected by automation; that is, a correlation exists between the two independent variables. Meanwhile, the endogenous variable "affected by automation" is a binary variable; thus, we use the generalized structural equation model (GSEM) to further analyze the mediating effects.

Figure 1 presents the results of the analysis of the mediating effects based on the GSEM. First, the results are consistent with the findings of existing studies. Individual employees affected by automation have higher levels of satisfaction with income, safety, and ability, which in turn affect their overall job satisfaction. However, the direct effect of the variable "affected by automation" on job satisfaction is not significant, thereby suggesting that job conditions such as income and safety are the key elements of the correlation between the two variables. Second, physical and mental stress and boredom at work significantly reduce job satisfaction, and employees in a position with high replacement stress due to automation experience a high degree of both effects, but the individuals affected by automation experience no significant effect on either path. The results support our study's presupposition that stress from automation produces two impact paths. In addition, the risk of replacement by automation has a negative effect on job ability and job satisfaction, which can potentially reveal the fact that automation has a restructuring effect on the overall work content of job positions. A position with a high level of automation adoption (replacement risk) is correlated with low satisfaction with job ability, which can reduce employees' overall job satisfaction.

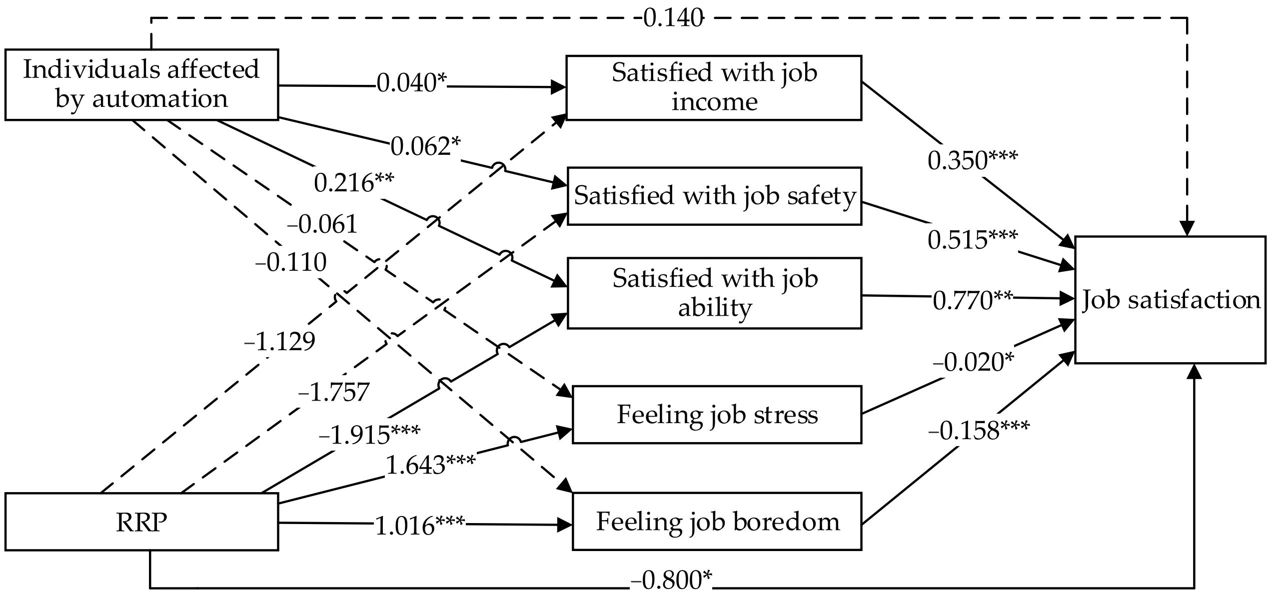

Figure 1. Analysis of the mediating effects of automation on job satisfaction (GSEM). Note: * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$; Solid lines indicate paths that are significant at the 95% confidence level, while dashed lines indicate insignificant paths at the 95% confidence level; data in the figure are non-standardized regression coefficients; model includes control variables.

4.4. Heterogeneity Analysis of Impact of Automation

In previous studies on the impact of automation on employment, automation technologies have heterogeneous effects on employees with different demographic characteristics, such as their age and education level and the skills and requirements for different positions [6,29,37]. Therefore, we further examine the heterogeneous effects of automation on job satisfaction in terms of employees' age, education level, job skills, and job requirements. Using the survey data, we categorize job skills into "high" and "low" groups based on whether the respondents have professional credentials. We group position competency and experience requirements according to the respondents' answers to the questions on their education level and the required work experience for their position. Specifically, we include the respondents with at least a high school certificate and 2 years of work experience in the "high" group of competency and experience requirements, and the respondents with an education level lower than high school and less than 2 years of work experience are put into the "low" group.

Table 4 presents the results of the heterogeneity analysis based on the demographic characteristics and position requirements. The results show that though the improvement and pressure effects of automation coexist, they act on different population groups in enterprises. The improvement effect of automation will likely be experienced by employees aged 35 years or below, with low job skills and low competency and experience requirements for their current position. The results are consistent with the finding that automation has a significant effect on the performance of young, low-skilled employees who typically have a poor, high-intensity, and low-competency position [16,37]. For employees over the age of 45 years with an education level of middle school or lower but certain job skills and position competency and experience requirements, replacement stress from automation plays a major role. We consider two possible explanations for this new finding. The first explanation is that elderly employees with specific job skills and experiences will be highly aware of automation characteristics and have a high perception of the risk of job replacement. The second reason is that such employees have high expectations of the value of their job. However, automation can have damaging effects on such expectations through job pressure and boredom.

Table 4. Heterogeneity analysis.

DV: Job Satisfaction	Age			Education		
	Age < 35 Years	35–45 Years	Age > 45 Years	Middle School or Below	High School	College or Above
Individuals affected by automation	0.178 *	0.091	0.109	0.146	0.166	0.097
	(0.080)	(0.089)	(0.105)	(0.089)	(0.105)	(0.079)
Positions affected by automation	−0.759	0.172	−1.270 **	−0.832 *	−0.063	−0.412
	(0.398)	(0.434)	(0.432)	(0.326)	(0.505)	(0.408)
CV	Yes	Yes	Yes	Yes	Yes	Yes
N	1163	828	1097	1305	687	1096
DV: Job Satisfaction	**Job Skills**		**Position Competency Requirements**		**Position Experience Requirements**	
	Low	**High**	**Low**	**High**	**Low**	**High**
Individuals affected by automation	0.138 *	0.125	0.152 *	0.093	0.174 *	0.085
	(0.063)	(0.090)	(0.063)	(0.092)	(0.075)	(0.071)
Positions affected by automation	−0.482	−1.634 *	−0.493	−0.903 *	−0.395	−0.905 *
	(0.270)	(0.536)	(0.303)	(0.456)	(0.302)	(0.368)
CV	Yes	Yes	Yes	Yes	Yes	Yes
N	2497	591	2215	873	1885	1203

Note: * $p < 0.05$, ** $p < 0.01$; data in the table are regression coefficients, with standard errors in parentheses; control variables are included in each subgroup model.

5. Discussion

Based on the 2018 CLDS data, this study examines the impact of automation on enterprise employees' job satisfaction on the individual and position levels. Through multiple analyses, we obtain several major findings.

First, we find that the individual employees affected by the implementation of automation have a high level of job satisfaction. However, having a position that will likely be replaced by automation reduces employees' job satisfaction. This finding illustrates that the paradox of the "improvement" and "replacement" effects of automation can exist simultaneously, and individual preferences and position characteristics jointly shape the impact of automation on employees' job satisfaction.

Second, besides the direct effects, replacement stress from automation can negatively affect job satisfaction through its mediating effect in the paths of job stress and boredom. Although automation is replacing heavy physical labor and improving the labor environment, its precision and standardization may lead to increased work intensity and the dissolution of the meaning of work. Therefore, in the context of technological replacement stress, automation can reshape the labor environment and shorten employees' stay in an enterprise in favor of autonomous and flexible jobs. This finding offers a potential explanation for the flow of the workforce from the manufacturing sector to the service sector, which is currently dominated by the platform economy.

Finally, from the perspective of the heterogeneous effects on different populations, we determine that the improvement effect occurs mainly among young employees and groups with low job skills and low position competency and experience requirements, whereas replacement stress affects middle-aged and elderly employees and groups with low education, high job skills, and high position competency and experience requirements. Automation, such as robotics, improves the working conditions and environment of young, low-skilled, and low-positioned employees and exerts a positive effect on employment integration for the group. As employees' length of work increases, moving into a position that requires considerable experience, competence, and skills will be possible; however, the replacement effect of automation will play a major role. This finding implies the negative impact on the internal labor market and the tendency to intensify the "short-termism" of employment in enterprises.

Based on the above findings, we provide several theoretical and practical implications for discussion. An increasing number of Chinese employees are shifting from traditional labor to digital labor [51,52], thereby indicating the "push and pull" effect of specific labor occupational mobility between industrial manufacturing enterprises and the platform economy. The transformation of the urban economy, from physical to digital, has created a large number of jobs in the platform service industry with flexible schedules and high income, thereby attracting new generations of migrant employees and accelerating their inflow from traditional industries [22,23]. Compared with the abundant discussions on and considerable attention paid to the psychological wellbeing of platform employees "trapped in the system" [22], the impact of automation technologies, such as automation, robotics, and AI, on employees in traditional enterprises should receive more attention. The findings of this study also reveal the "hidden cost" of automatic technology development, in which a balance exists between job replacement and job creation, but work psychological wellbeing is reduced for society as a whole.

Although many studies emphasize the need to strengthen skill-oriented education and training for employees in response to the trend of "Replacing Humans with Machines" [2,8,21], this approach may not necessarily improve employees' chances of staying in traditional enterprises. Enterprises, labor unions, and labor authorities should consider the inevitable impact of the widespread use of automation on employees, especially on their mental health and satisfaction. Therefore, in the development and popularization of automation, the authorities should strengthen the construction of an internal labor market growth system that can enrich employees' autonomy, creativity, and psychological empowerment and make full use of psychological guidance and intervention from enterprise social work to actively improve employees' feelings of labor acquisition and job satisfaction.

The current study has limitations that need further research. Firstly, regarding measurements, this study builds on a national survey conducted in 2018 in China; however, there was only one question measuring the perceived impact of automation, future research could add objective measures of the impact of automation use. In addition, we only use one item to measure overall job satisfaction; although a number of previous studies have proven its stability, future research can measure job satisfaction from multiple dimensions to increase the validity. Secondly, from a sampling perspective, since the survey was only conducted in 2018, this is not a panel survey that allows us to observe the changing effect of automation and job satisfaction. Further studies could address the longitudinal effect between these two variables. Despite these limitations, we believe that this study can serve as inspiration for subsequent research, given the significant societal trend of automation. It highlights the need for automation studies to extend beyond economic impacts and underscore the overall welfare of society. The ongoing attention to social welfare issues arising from technological advancement remains crucial.

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