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Research article

Impact of digital empowerment on labor employment in manufacturing enterprises: Evidence from China

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A B S T R A C T

Many studies have examined the influence of digital technologies, such as robots and artificial intelligence, on enterprise labor, but few have investigated the underlying mechanisms and impact paths of digital empowerment on labor employment. Therefore, this study uses data on manufacturing enterprises listed on China's Shanghai and Shenzhen A-share markets from 2011 to 2020, and applies a panel fixed effect model to test the relationship between digital empowerment and labor employment, and the mechanisms underlying this relationship. We find that digital empowerment increases labor employment. However, the effects are heterogeneous: firms with better corporate governance, more competitive industry, and less favorable regional business environments are more motivated to optimize the structure of their labor resources. Through robustness test and mediation effect model test, we find that digital empowerment can improve enterprise human capital by increasing economies scale and managerial efficiency, especially the employment of R&D and innovation personnel and management personnel; it can also affect the amount of human capital by improving total factor productivity.

1. Introduction

The new generation of digital technologies and their applications have brought new economic opportunities for the real economy, while the digital economy has become a major driving force for high-quality economic development in countries around the world [1–3]. Furthermore, the deep integration of digital empowerment and the real economy can help accelerate the digital transformation of industry. In particular, digital empowerment has become a key engine for companies to access new opportunities and paths for growth [4–6]. According to the Digital China Development Report (2022) released by the National Internet Information Office, China's digital economy is 50.2 (7.2) trillion yuan (dollars) in 2022, ranking second in the world. Meanwhile, the Research Report on the employment impact of the digital economy issued by the China Academy of Information and Communications Technology (CAICT) in 2021 points out that the number of jobs driven by the digital economy will reach 379 million by 2025. Digital economy have played an

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important role in stabilizing employment and promoting development [7,8].

However, some researchers [9,10] suggest that the development of the digital economy will also reduce the demand for traditional workers in enterprises. Meanwhile, many multinational companies, such as Pfizer and Apple, are facing the problems (e.g. rising labor costs) while embracing digitalization. To achieve quality growth in the new trade environment, they are also looking to reduce labor costs and improve workforce quality through digital transformation and multi-regional layoffs. However, to leverage the advantages of digital empowerment, high-quality labor resources are also required besides machine automation and smart manufacturing equipment. Moreover, readjusting the firm's business structure and direction requires new labor resources during the process of digitalization. Therefore, based on the impact mechanism of digital empowerment on labor employment, fully utilizing technical resources to make up for the partial lack of labor resources remains a key issue for enterprises.

Studies are increasingly recognizing the coexistence of the substitution [11,12] and creation effects [13–18] of the digital economy on the labor market. Some scholars also argue that digital empowerment changes the structure of labor employment and not just the number of employees [19–26].

Digital empowerment, whether it comes from digital industrialization or industry digitization, has the potential to change, or even disrupt, the human resource framework of enterprises. The extant literature [11–13,17,24,25] mainly studies the impact of the digital economy on labor demand, employment, and factor allocation from the industry level. However, research from the corporate governance level, especially theoretical and logical explanations, is scarce. Furthermore, it is not enough to focus on the underlying mechanisms from a production level; we also need to focus on the management level.

This study seeks to address these gaps and asks the following questions.

(1) Does digital empowerment increase or decrease labor employment in firms?
(2) Does digital empowerment have the same impact on the employment of different enterprises?
(3) What is the pathway through which digital empowerment affects corporate employment?

Our work makes the following contributions. First, we study the impact of digital empowerment on labor employment at the micro level of corporate governance, which is a meaningful supplement to previous studies that have mostly focused on the macro level. Second, we provide a finer understanding of the effects of digital empowerment on hiring by showing its heterogeneous impacts by various firm characteristics, such as ownership, competitive structure of the industry, and regional business environment. Third, we shed light on the underlying mechanisms through which digital empowerment affects firm hiring. We empirically test the mediating effects of managerial efficiency, economies of scale, and total factor productivity.

2. Literature review and hypotheses development

2.1. Literature review

2.1.1. Digital empowerment

Numerous studies have examined digital empowerment and outlined their own definitions of what it means. Hermansson and Mårtensson argue that emerging big data, mobile Internet, and artificial intelligence (AI) technologies can empower people to cope or solve problems, and call this process digital empowerment [27]. Lenka et al. believe that enterprise digital empowerment capabilities include three fundamental subcomponents: intelligence, connectivity, and analytics capabilities, which synergistically improve an enterprise's ability to acquire, analyze, and use data, and create value with customers through sensing and response mechanisms [28]. Examining organizational management, Sun et al.summarize data empowerment as the process of updating and iterating the scenarios, technologies, and methods of data use to realize the value of data [29]. Lv and Li propose the following process of digital technology empowerment: "connect-mine-optimize, control-increase efficiency" [30]. The authors believe that digital technologies, such as the Internet of Things (IoT), can be used to connect the upstream, midstream, and downstream of the value chain, accelerate the collection and application of data, and then empower the production function of enterprises to improve their efficiency and capability. Finally, Zhang et al. define digital empowerment as the comprehensive integration of technology, organization, production, and management driven by digital technology [31]. This enables enterprises to rearrange factor combinations to establish new production functions, thereby enhancing production efficiency.

As shown, digital empowerment has different definitions and meanings. At the enterprise level, digital empowerment has many manifestations, such as "digital financial inclusion", "artificial intelligence", "information and communication technology", "Internet application", "digital infrastructure". Nevertheless, there are two points of consensus on its meaning: First, the existence of data does not automatically enable the user to gain additional value. The user needs to acquire or enhance capabilities, or gain knowledge necessary for value creation through data acquisition, analysis, and application [29]. Second, digital empowerment tends to focus on the whole at the system-level.

Synthesizing this literature, we define digital empowerment as follows: digital empowerment can be derived from the development of information technology and its application; it is the process of ultimately realizing the value of digital empowerment itself through the scenarios, technologies, and methods of data acquisition, analysis, and application, thereby providing users with the necessary knowledge (such as opportunities and resources) for capability acquisition or enhancement, and value creation.

2.1.2. Labor employment

The conceptual terms of labor and employment are relatively simple, and have widely accepted definitions. In a broad sense, labor refers to the entire population, while in a narrow sense, labor refers to the population with labor capacity. The labor force that individuals of working age, with the ability and willingness to work, engage in certain social labor and receive corresponding labor remuneration is called labor employment, including employees, self-employed, contributing family workers, etc.

As a article researching business management issues, the employment relationship refers to the legal relationship in which both parties agree that the "employees" works for the "employer" and the employer provides compensation.In the business world, enterprises obtain commercial profits through output behaviors. Those who engage in such output behaviors and obtain income from them are called employees/staff. The labor force who has signed an employment contract is called labor employment.

Improving population quality and transforming from demographic dividend to talent dividend are strategic decisions for China's current population development, which requires sustained investment in human capital [32]. In 2021, the average number of years of education for China's newly added labor force reached 13.8 years, and higher education has entered the universally recognized stage of popularization. At the same time, the rapid development of the digital economy has strengthened the demand for highly skilled talents in Chinese manufacturing enterprises [33]. In addition, limited by space, this study focuses more on high-quality labor force; that is, highly educated personnel. Intuitively, our measure for the labor employment then become the number of employees who have received higher education.

2.1.3. The impact of digital empowerment on enterprise labor employment

Scholars have different views on the effect of digital empowerment on labor employment. First, some consider that digital empowerment has a substitution effect on enterprise labor employment. As early as 1930, the economist John Maynard Keynes predicted that "technological unemployment" would occur in a hundred years. Indeed, Decker et al. have expressed concerns about the replacement of labor by service robots [34]. Acemoglu and Restrepo show that technological advances will lead to lower labor demand if the positive stimulus of productivity growth is not sufficient to offset the labor displacement effect of automation [11,12]. Furthermore, the overall substitution effect of robots on the labor force of Chinese firms was approximately 2.6% during 2015–2017, and approximately 0.3 percentage points on the Chinese labor market as a whole [35]. Notably, low-skilled jobs in China's manufacturing sector are being or will soon be replaced, and structural unemployment is still possible [10].

In addition, the reshaping of traditional skills has led to the shortening of employment contracts between firms and workers [36]. Workers on fixed-term contracts face a higher risk and a not-so-short period of unemployment compared to workers on regular contracts [37]. In particular, flexible temporary employment traps populations such as women and less-educated individuals in a cycle of repeated temporary employment [38,39].

Second, others suggest that digital empowerment can have a job creation effect. Although the number of ATMs reached over 400,000 in the US in 2010, the number of bank employees did not decrease accordingly [13]. Furthermore, technological advances have led to increased productivity and lower prices of goods, while the demand for products or even related products has increased significantly [14]. The adoption of robots may also increase the demand for complementary non-automated tasks [7]. Government intervention and policy changes can help reduce the impact of technological advances and that technological advances lead to a large number of new jobs; thus, large-scale human-machine replacement may not occur [40]. Acemoglu and Restrepo [15] show that the internet and digital technologies can improve the efficiency of labor factor allocation by reducing spatiotemporal barriers and enriching employment options; consequently, automation may contribute more to job creation than destruction. Furthermore, some researchers argue that employment demand driven by technological progress will offset some of the substitution effect, while total employment demand will increase [16,17,41]. AI may trigger a rise in short-term unemployment, but will not weaken aggregate labor demand [42]. Similarly, technological advances may reduce (increase) employment in the short (long) run [43,44]. Digital economy significantly expands the labor demand of enterprises [18], and has a evident positive effect on the employment scale in China [45].

Meanwhile, constraints can induce enterprises to reduce labor employment [46,47]. However, the rapid development of digital finance can reinvigorate the job market, especially for weaker and smaller firms, and regions with lower urbanization [48]. Digital finance development promotes entrepreneurship and off-farm re-employment by increasing the social trust of farmers [49,50]. Digital economy has not only created a large number of jobs, but also fostered more flexible labour relations and working patterns [51], such as "internet celebrities" and "gig economy" [52]. Digital platforms promote employment in poor areas through e-commerce consumption [53]. Some scholars [54,55] believe that crowd sourcing tasks through digital platforms can create employment opportunities for the working population and even the disabled [56] in developing countries. Networked consumption and transactions provide numerous free work opportunities for low-skilled labor [57].

Third, some posit that digital empowerment not only changes the number of workers, but also has a profound impact on the structure of the workforce. The advent of the digital age has dramatically changed employment relationships, with a shift from offline to online, human to machine, fixed to flexible, and single to multiple jobs [58]. The emergence of online labor marketplaces and "gig economy" platforms with new employment forms, such as app-based on-demand work, has improved job matching and created many new jobs and forms, while also accelerating the demise of some existing jobs [19,20]. Digital economy increases (decreases) high-tech-intensive (labor-intensive and medium-tech-intensive) employment [22]. Similarly, the process of enterprise digital transformation significantly increases the demand for technical, service-oriented, and high-skilled employees, while creating a obvious substitution effect for productive and low-skilled employees, and these employment structure effects are more pronounced in large-scale enterprises, state-owned enterprises, and the eastern region [23]. The development of the digital economy can effectively improve the employment structure by improving the industrial structure, but there is heterogeneity, which is influenced by degree of marketization, geographical location, level of economic development, and whether it is located in coastal areas [24]. Meanwhile, the impact of the digital economy development on the employment structure is more significant on the secondary and tertiary industries than in the primary industry. Digital reform reduces the labor demand of the primary and secondary industries, and increases the labor demand of the tertiary industry [44,59]. However, the impact of the digital economy on employment in the secondary industry exhibits an "inverted U-shape" characteristic [25,26], the impact presents a "positive U-shape" characteristic at the trade and skill levels [25], but the impact presents a "positive U-shape" characteristic in the primary industry [26].

Technological advances in the US since 1980 have caused employment polarization, the brunt of which has been experienced in the form of a decrease in middle-skilled jobs [60]. This is contrary to an increase in high- and low-skilled jobs [7,17]. Numerous studies have found that labor market polarization is particularly prominent in developed countries. The adoption of robots significantly boosts firms' hiring of high-skilled talent [61]. The creation and substitution effects of automation on the labor market almost cancel each other in Chile; however, the jobs were mainly created for high-skilled people, while low-skilled people faced a higher risk of unemployment [21]. The same situation also exists in China [62–64]. However, some researchers argue that employment polarization is not clear in many developing countries; for example, in China, the share of middle-skilled labor is increasing, while that of low-skilled labor is decreasing rapidly [65].

In summary, research on employment in the digital economy has developed to some extent, mainly focusing on labor demand, employment, and labor factor allocation in the digital economy. Moreover, there is increasing recognition that the digital economy has both substitution and creation effects on the labor market. However, to the best of our knowledge, there are few in-depth studies on the impact of digital empowerment on labor force employment from a corporate governance perspective, especially theoretical and logical explanations. Furthermore, it is not enough to focus on the underlying mechanisms at the production level; we should also focus on the managerial level. Here, we seek to address these gaps.

2.2. *Hypotheses development*

Digital empowerment is based on the development of information technology, its application, and the reproduction of information technology capital. As defined earlier, digital empowerment is the process of identifying and utilizing big data resources through the scenarios, technologies, and methods of data acquisition, analysis, and application to provide users with the necessary knowledge (such as opportunities and resources) for capability acquisition or enhancement, and value creation, thereby realizing the value of digital empowerment. This theoretical definition implies that a firm's degree of digital empowerment is related to its workforce. Some scholars have examined the underlying mechanisms through which digital empowerment of enterprises affects labor employment.

First, digital empowerment has a job substitution effect [11,12]. Enterprises use intelligent software and machines to digitize some simple, repetitive, and boring work. Consequently, they can increase firms' service human capital, promote the service of inputs, reduce the human input in the production process, improve the output of unit labor, and enhance labor efficiency.

Second, digital empowerment has a labor resource reallocation effect [49,50]. Specifically, enterprises can integrate and reproduce resources from and in different fields, focus on user hotspots, quickly respond to new consumption, enhance cross-border competitive and operational capabilities, coordinate business ecology, balance stakeholders, reduce production costs, and form new business competition models. That is, the role of labor resources in the process of digital empowerment of enterprises will change. Consequently, firms will experience new requirements for labor quality, and in adapting to consumer-led production and digitalization. Labor that cannot adapt to the requirements of business transformation will be either optimized or made redundant.

Third, digital empowerment of enterprises will induce changes in the production process [20,58]. Specifically, digital technology applications will increase machine production, especially intelligent production. For example, the application of IoT may increase the possibility of substituting shop floor workers with intelligent machine-based production. Meanwhile, to adapt to the big data processing technology, cloud computing, 5G, and other technologies, enterprises will need to undertake digital transformation, technology upgrades, and technology overflow, which will require more research and development (R&D) personnel [22,23].

Fourth, the digital empowerment of enterprises will impose higher requirements on the firm's management [66]. Specifically, the management of more skilled workers will need more professional intellectual capital, while the management of smarter production lines will need more technical capital. Together, this will impose greater demands on management personnel to adjust the strategic structure of enterprises [67].

Based on these arguments, we propose the following hypotheses.

H1a. The higher the degree of digital empowerment of the enterprise, the more it will reduce the overall employment volume.

H1b. The higher the degree of digital empowerment of the enterprise, the more it will increase the employment of high-quality labor.

Enterprise digital empowerment also triggers the secondary distribution of labor resources. Specifically, it involves realizing further integration, sharing, and co-creation of data resources through the optimization of labor resources.

First, digital empowerment may improve managerial efficiency [66,68]. Digital empowerment can reduce the cost of internal coordination through information technology [69]. This will help enhance operational efficiency through automated management, thereby reducing the supervision and employment costs related to middle management. Ultimately, this will promote lower hiring. Furthermore, information technology can reduce the barriers and costs of internal communication, promote flattening and platforming within the firm, use cross-network externalities to establish cross-border competitive advantages in multilateral markets, enhance financial leverage capabilities, and improve enterprises' risk resistance. This will also reduce labor hiring. Finally, the traditional management model has changed in two ways. First, firms are increasingly transforming from being labor-to capital-intensive; this puts higher demands on labor hiring. Second, managerial efficiency improvements due to the platform effect mean that firms are increasingly moving from vertical to flat management; this reduces ordinary hiring and increases managerial hiring.

Second, digital empowerment can bring economies scale [18,45]. Through digital technologies, enterprises can quickly gain scale by expanding their data advantages and then target more customized consumer experiences, increase their foothold in cross-border markets, and sell directly to consumers. Thus, firms can break the spatial and temporal boundaries imposed by traditional market barriers as well as reduce the number of front-line salesmen and market researchers who directly interface with consumers. Moreover, digital empowerment enables efficient processing and integration of internal and external firm information resources. Together with IoT and big data analytics, a firm which is larger and has more data resources can have better asset turnover. Consequently, firms will require new workers to accommodate new production lines. In addition, digital empowerment can also induce multi-faceted or even cross-border data cooperation, which can expand markets and help the firm scale. In this situation, the non-competitive nature of data makes the processing and application of data more complex and urgent. This will require more technical personnel to complete the flow, transformation, and allocation of digital resources and value realization.

Third, digital empowerment can enhance total factor productivity [70,71]. Enterprise digital empowerment drives agile manufacturing and technological innovation. This optimizes resource allocation efficiency and information accessibility, which play a mediating effect in the impact of digitization on enterprise resilience, further promoting the growth of total factor productivity and high-quality development of the manufacturing industry [72]. Especially for small and medium-sized enterprises, data-driven dynamic capabilities is a key driving force for improving sustainable development performance [73]. Moreover, the allocation of data resources cannot be separated from digital empowerment. Digital transformation can enhance firms' innovation performance [74], as well as improve the success of innovations by making the innovation efforts more purposeful and directional. This innovation can be more in line with consumer preferences and market demand, thereby further improving total factor productivity. Then, this increase in the total factor productivity will require enterprises to have a correspondingly high-quality workforce.

Based on these arguments, we propose the following hypotheses.

H2a. Digital empowerment reduces labor hiring by improving managerial efficiency.

H2b. Digital empowerment increases labor hiring through better economies scale.

H2c. Digital empowerment improves labor hiring by increasing total factor productivity.

3. Research design

3.1. Data source and sample selection

We used data on A-share listed manufacturing companies on the Shanghai and Shenzhen stock exchanges in China from 2011 to 2020. These data were obtained from the China Stock Market & Accounting Research Database (CSMAR); financial data were obtained from the listed companies' financial statements, while data on digital indicators were obtained from the listed companies' digital economy research data. To ensure the validity of the data, the following data were deleted: delisted companies; ST (companies that have been delisted due to abnormal circumstances such as consecutive losses for two years), *ST(companies that have been delisted due to abnormal circumstances such as continuous losses for three consecutive years), and PT (implement special transfer services for companies that have been suspended from listing) companies; and samples with abnormal and seriously missing data. The reports of listed companies are generally strict and complete, missing values are more likely to occur randomly. On average, the proportion of missing values for each variable is only about 1%, so the sample data with missing values was directly deleted. Finally, to mitigate the influence of extreme values, we winsorized the values for all variables at the 1% and 99% of their distributions. Consequently, a total of 1055 A-share listed manufacturing companies left.

3.2. Variable definition and descriptions

3.2.1. Dependent variable

The main explained variable, labor force employment (Labor), is represented by human capital (lnhumans), which is measured by the natural logarithm of the number of employees with higher education. In addition, we test the robustness of results using the natural logarithm of the number of all employees (lnlabor) [75], R&D staff (lnrdp), and management staff (lnManager).

3.2.2. Independent variable

The main explanatory variable is digital empowerment (DT). Following Yuan et al. [76], First of all, use the semantic expressions of national policies related to the digital economy, after Python word segmentation and manual recognition, 197 enterprise digitalization related vocabulary words with a frequency greater than or equal to 5 times were finally selected, which constitute the enterprise digitalization terminology dictionary, such as AI Technology, Block Chain Technology, Cloud Computing Technology, Big Data Technology, and Digital Technology, among others. Secondly, expand the above 197 vocabulary words to the "jieba" Chinese word library of the Python software package, use a text analysis method based on machine learning to analyze the relevant paragraphs of enterprise annual reports, and calculate the frequency of the digital related vocabulary obtained in the first step appearing in the annual reports. Thirdly, divide the digital empowerment indicators in the second step by 100 to obtain the numerical values of the enterprise digital empowerment indicators for our article.

3.2.3. Control variables

The control variables are enterprise size, age, solvency, operating capacity, profitability, and innovation capacity, and relative value indicators. Enterprise size (Scale) generally refers to the size of the enterprise, which can be measured based on the number of employees or the amount of assets. In this article, the natural logarithm of the total assets is used to represent the enterprise size. Enterprise age (Age) is the natural logarithm of the number of years from the date of establishment. Enterprise solvency is a summary and evaluation of important indicators of enterprise's financial position and operating results, we choose the ratio of total liabilities to total assets (ROA) to represent enterprise solvency. Enterprise profitability refers to the amount and level of its earnings during a certain period of time, expressed as the ratio of net income to the balance of shareholders' equity, which is the return on equity (ROE). Enterprise operating capacity means the efficiency and effectiveness of its operational assets, represented by capital intensity (CIR), which is the ratio of total assets to operating income. Enterprise innovation capacity is usually measured by the amount of investment or output in research and development, our article uses the natural logarithm of the R&D investment amount (RDS) on behalf of enterprise innovation capacity. Finally, the relative value of the firm is expressed using the widely used TobinQ, which is an evaluation of the company's growth prospects by the stock market, and is calculated as market value/(total assets - net intangible assets - net goodwill).

3.3. Model setting

Our regression model is as follows:

$$\ln humans_{it} = \beta_0 + \beta_1 DT_{it} + \gamma_1 Control_{it} + \varepsilon_{\text{it}} \tag{1}$$

To test the channels through which digital empowerment affects labor force hiring, we refer to the mediating effects model established by Baron and Kenny, and Wen et al. [77,78], and set up the following model:

$$Mediator_{it} = \beta_2 + \beta_3 DT_{it} + \gamma_2 Control_{it} + \mu_{\text{it}} \tag{2}$$

$$\ln humans_{it} = \beta_4 + \beta_5 DT_{it} + \beta_6 M\text{ediator}_{it} + \gamma_3 \text{Control}_{\text{it}} + \upsilon_{\text{it}} \tag{3}$$

where the subscript i denotes the firm, t denotes the year, ε is the error term, β and γ are the coefficients to be estimated, $lnhuamns_{it}$ denotes the firm labor force employment, DT_{it} denotes digital empowerment, and $Control_{it}$ denotes the control variables. Furthermore, we use a panel fixed effects model and control for individual, year, industry, and regional effects. Next, we use the natural logarithm of firm sales to represent the economy of scale (Sales) indicator [79]. Finally, referring to Ackerberg et al. [80], total factor productivity is calculated using the Ackerberg-Caves-Frazer modified OP method. The logarithmic form of the C-D production function is as follows:

$$ln\ Y_{it} = \alpha_0 + \alpha_1\ ln\ L_{it} + \alpha_2\ ln\ K_{it} + \alpha_3\ ln\ M_{it} + v_{it} \tag{4}$$

4. Empirical test and results

4.1. Descriptive statistics

Table 1 reports the descriptive statistics for main variables. Labor force employment has a mean of 6.010 and a standard deviation of 1.09. Notably, the mean, minimum, and maximum of the total number of employees are 7.920, 3.330, and 12.09, respectively, indicating a large disparity between firms. The mean value of digital empowerment of enterprises is 0.070, with minimum and maximum values of 0 and 2.9, respectively. This indicates that the digitalization of Chinese enterprises is relatively low, with limited differences across firms. Meanwhile, all other indicators show the difference in capability among enterprises.

Table 1
Descriptive statistics of variables.

Variable	Mean	SD	Min	Max	p50	N
lnhumans	6.010	1.090	1.500	9.540	5.940	9481
lnlabor	7.920	1.050	3.330	12.09	7.850	9481
lnrdp	3.460	2.970	0	9.680	4.800	9481
lnManager	1.810	0.360	0	3.140	1.790	9481
DT	0.0700	0.180	0	2.900	0.0100	9481
Scale	22.20	1.070	20.09	25.73	22.09	9481
ROE	0.0700	0.0800	−0.430	0.310	0.0600	9481
AGE	2.750	0.400	0.690	3.810	2.830	9481
RDS	17.01	4.490	0	21.88	17.99	9481
ROA	0.400	0.180	0.0500	0.800	0.390	9481
CIR	2.050	1.300	0.210	21.85	1.750	9481
TobinQ	2.060	1.150	0	8.290	1.720	9481
Manage	0.170	0.110	0.0200	0.600	0.130	9481
Sales	21.57	1.240	18.75	25.37	21.46	9481
opacf	8.670	0.600	6.830	12.14	8.620	9481

4.2. Correlation test

In Table 2, we provide the results of the correlation test for all variables. The variance inflation factor (VIF) is used to test multicollinearity. Notably, all VIF values are less than 5, which indicates that there is no multicollinearity problem. Next, the correlation test results show that all variables have significant correlation with the explained variable lnhumans. This provides evidence for the scientific validity of later regression results.

4.3. Linear panel regression analysis

Using the Fisher unit root test method to perform unit root tests on all dependent and independent variables, the results showed that the p-values were all less than 0.01, indicating that our data is stationary. Next, to determine the validity of our regression model, we conducted a Hausman test, which yielded $\chi^2(8) = 61.83$ and Prob $> \chi^2 = 0.0000$. These results suggest that a fixed effects model should be used. Table 3 shows the regression results using the panel fixed effects model. Column (1) shows that for each unit increase in digital empowerment, the firm's labor force employment significantly increases by 0.0936 units ($p < 0.01$). Meanwhile, column (2) shows that digital empowerment does not significantly affect the overall labor force hiring ($p > 0.1$). Column (3) shows that each unit increase in digital empowerment significantly increases the demand for R&D personnel by 0.2574 units ($p < 0.01$). Column (4) shows that each unit increase in digital empowerment significantly increases the demand for managers by 0.0575 units ($p < 0.01$). Thus, hypothesis H1a is rejected, and hypothesis H1b is supported.

In addition, intuitively, we find that a larger firm size has more employees. Further, the greater the firm age, the larger its size. Meanwhile, firm capital intensity and return on net assets are inversely related to firm labor hiring, which is related to the substitution effect of capital and labor. Furthermore, firms with higher levels of innovation have stronger growth potential to expand capacity and increase high-quality human capital employment. Finally, the stock market's bullish outlook and rising relative value of firms help them expand their workforce.

4.4. Robustness tests

Due to the fact that only listed companies with publicly available data can be selected as analysis samples, while non listed companies are ignored, there is a problem of sample selection bias. To mitigate sample selection bias concerns, we conduct an endogeneity test using the Heckman two-stage method [81]. The results are reported in columns (1) and (2) of Table 4. Column (1) shows the results of the regression estimation of the percentage of highly educated employees as a percentage of overall employees using a Probit-model based selection equation; through this, we obtain the inverse Mills ratio (imr). Column (2) then regresses this ratio on human capital; the results show that the inverse Mills ratio is significant at the 1% level, indicating the existence of sample selection bias and justifying our use of the Heckman two-stage method to control for sample selection bias. Substituting again and regressing with the panel data fixed effects model, column (2) also reports a significantly positive coefficient of digital empowerment (0.4113, $p < 0.01$). This is consistent with our previous estimation results and indicates that digital empowerment promotes higher quality of labor hiring.

Meanwhile, firms efforts to enhance human capital may also drive them to be more digital empowered; this may lead to two-way causality. Indeed, using the Durbin-Wu-Hausman (DWH) test reveals that there may be an endogeneity problem between digital empowerment and labor force hiring (6.856, χ^2 (1) $p = 0.0088 > 0.0035$). Consequently, we use an instrumental variable method to overcome this, Zhao et al. [70] verified the effectiveness of the number of users with Internet access and the number of urban mobile phones as the instrumental variables of digital empowerment, instrumental variables meeting the requirements of exclusion restriction and correlation. Since enterprises' digital business is more concentrated on the computer side than on mobile phones, our paper selects the number of users with Internet access as the instrumental variable of digital empowerment. Column (3) of Table 4 reports the estimation results using the total number of users with Internet access in a year in the province where the firm is located as the instrumental variable. The two-stage least squares-instrumental variables method test yields an F-statistic of 208.25 and a Kleibergen-Paap rk LM statistic of 35.579. Next, χ^2 (1) $p = 0.0000$ passes the under-identification test. Further, the Kleibergen-Paap rk Wald F-statistic of 31.671 is greater than Stock-Yogo weak ID test value of 16.38 at the 10% level, thus passing the weak instrumental

Table 2
Results of correlation test.

Variable	VIF	lnhumans	DT	Scale	ROE	AGE	RDS	ROA	CIR	TobinQ
lnhumans		1								
DT	1.02	0.067***	1							
Scale	1.72	0.774***	0.048***	1						
ROE	1.23	0.169***	−0.0160	0.127***	1					
AGE	1.11	0.192***	0.028***	0.278***	−0.029***	1				
RDS	1.07	0.197***	0.099***	0.212***	0.046***	0.068***	1			
ROA	1.58	0.403***	−0.00500	0.521***	−0.127***	0.222***	0.0150	1		
CIR	1.14	−0.216***	0.044***	−0.058***	−0.241***	−0.060***	−0.0160	−0.179***	1	
TobinQ	1.19	−0.176***	0.057***	−0.282***	0.186***	−0.0160	0.0140	−0.277***	0.036***	1

Note: *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

Table 3
Linear panel regression results.

Variable	(1)	(2)	(3)	(4)
	lnhumans	lnlabor	lnrdp	lnManager
DT	0.0936***	−0.0012	0.2574***	0.0575**
	(2.880)	(-0.041)	(2.936)	(2.428)
Scale	0.6829***	0.7183***	0.6401***	0.0670***
	(39.099)	(45.832)	(17.703)	(6.307)
ROE	−0.2609***	−0.4008***	−0.2344	0.0550
	(-3.582)	(-6.090)	(-1.344)	(1.173)
AGE	0.1484***	0.1480***	0.1965	−0.1553***
	(2.696)	(3.424)	(1.539)	(-4.576)
RDS	0.0042**	0.0028**	0.0440***	0.0017**
	(2.538)	(2.418)	(8.308)	(2.128)
ROA	0.0127	0.0633	−0.0155	0.0079
	(0.231)	(1.322)	(-0.136)	(0.231)
CIR	−0.0773***	−0.1131***	−0.1001***	−0.0062
	(-10.903)	(-16.319)	(-7.465)	(-1.431)
TobinQ	0.0144***	0.0136***	−0.0138	0.0036
	(2.975)	(3.416)	(-1.154)	(1.208)
Constant Term	−9.4949***	−8.2802***	−11.8025***	0.7175***
	(-24.820)	(-24.959)	(-14.410)	(3.086)
Firm Effect	Controlled	Controlled	Controlled	Controlled
Time Effect	Controlled	Controlled	Controlled	Controlled
Regional Effect	Controlled	Controlled	Controlled	Controlled
Industry Effect	Controlled	Controlled	Controlled	Controlled
N	9467	9467	9467	9467
R^2	0.9150	0.9436	0.9315	0.6956
adj. R^2	0.9038	0.9362	0.9225	0.6556

Note: t-statistic values are in parentheses.*$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

variable test. The regression results show that the estimated coefficient of digital empowerment is still significantly positive (1.6674, $p < 0.05$). Thus, our results suggest that the impact of digital empowerment and corporate labor force hiring is robust.

Next, in column (4), we use an alternative method to compute digital empowerment. Specifically, we use the coverage breadth indicator (DII) in the Digital Inclusive Finance Index published by Peking University [82]. This indicator refers to the coverage rate of digital financial accounts, including the number of Alipay accounts per 10,000 people, the proportion of Alipay card-tied users, and the average number of bank cards tied to each Alipay account; this represents the basic digital level of enterprises in a local area to a certain extent. Again, the estimated coefficient of digital empowerment remains significantly positive, with each unit increase in digital empowerment increasing corporate labor hiring by 0.0031 units.

Next, in column (5), we remove the anomalous data due to the European debt crisis in 2011 and COVID-19 in 2020, and re-run the regression. Again, the estimated coefficient of digital empowerment is significantly positive (0.0954, $p < 0.01$).

Column (6) tests the causal identification of impact of the "Broadband China" policy. In August 2013, the State Council of China issued the "Notice of The State Council on the Issuance of the 'Broadband China' Strategy and Implementation Plan" according to the requirements of the "National Informatization Development Strategy 2006–2020". The Ministry of Industry and Information Technology, and the National Development and Reform Commission selected a total of 120 cities (groups) as "Broadband China" demonstration sites in three batches in 2014, 2015, and 2016 to raise broadband access capacity, broadband user penetration rate, and other aspects to the national leading level. We use a DID method to solve the potential endogeneity problem from this policy. Enterprises in cities with and without Broadband China policies are used as the treatment (Treat variable = 1) and control groups (Treat variable = 0), respectively. The Post variable is assigned a value of 1 in 2014, 2015, and 2016, the years in which the policies were implemented, and a value of 0 in the remaining years. The estimated coefficient of Treat*Post is significantly positive, indicating that digital empowerment of enterprises positively affected labor employment.

4.5. Heterogeneity test

The effect of digital empowerment on labor employment can be influenced by various factors, especially corporate ownership, competitive differences across industries, and the regional market environment where the enterprise is located. Here, we discuss this heterogeneity in the impact of digital empowerment on labor employment under the three aforementioned conditions.

Table 5 reports the regression results. Columns (1) and (2) consider the magnitude of the firm's market power using the Herfindahl-Hirschman Index (HHI): an HHI greater than or equal to 0.1 represents an oligopolistic market structure, and less than 0.1 represents a competitive market structure. The results show that the estimated coefficient of digital empowerment digital empowerment is significantly positive in both competitive (0.0815, $p < 0.05$) and oligopolistic (0.1366, $p < 0.1$). Thus, firms with existing competitive advantage may have more incentives to enhance their human capital to increase their competitive advantage.

Columns (3) and (4) considers the influence of state ownership. Interestingly, the estimated coefficient of digital empowerment for state-owned enterprises in column (3) is not significant, while it is significantly positive (0.0864, $p < 0.01$) for non-state manufacturing

Table 4
Robustness test regression results.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Heckman two-stage method		2SLS-IV	Replace core explanatory variables	Eliminate abnormal samples	Identification of causality of "Broadband China" policy
main						
DT	0.8671***	0.4113***	1.6674**		0.0954***	0.0884***
	(9.364)	(3.705)	(2.375)		(2.591)	(2.729)
Scale	0.0404**	0.7082***	0.6110***	0.6862***	0.6518***	0.6832***
	(2.520)	(37.171)	(16.484)	(39.396)	(32.984)	(39.199)
ROE	0.2443	−0.1474*	−0.2068**	−0.2544***	−0.3157***	−0.2559***
	(1.302)	(-1.791)	(-2.430)	(-3.515)	(-4.388)	(-3.513)
AGE	0.0572*	0.1751***	0.0367	0.1486***	0.1140*	0.1526***
	(1.647)	(3.145)	(0.445)	(2.713)	(1.722)	(2.773)
RDS	0.0072**	0.0082***	0.0042**	0.0044***	0.0077***	0.0043**
	(2.380)	(3.855)	(2.363)	(2.634)	(3.699)	(2.565)
ROA	−0.5012***	−0.2527**	−0.0755	0.0130	0.0139	0.0081
	(-5.492)	(-2.500)	(-1.056)	(0.238)	(0.237)	(0.148)
CIR	0.1105***	−0.0298*	−0.0739***	−0.0771***	−0.0681***	−0.0771***
	(10.106)	(-1.699)	(-9.875)	(-10.897)	(-8.982)	(-10.908)
TobinQ	0.0544***	0.0416***	0.0117*	0.0144***	0.0108**	0.0143***
	(4.385)	(4.190)	(1.952)	(2.980)	(2.182)	(2.947)
imr		0.8255***				
		(2.995)				
Digital				0.0031***		
				(4.784)		
TreatPost						0.0441***
						(3.158)
Constant Term	−1.3837***	−10.9359***		−10.3093***	−8.7782***	−9.5277***
	(-4.260)	(-18.199)		(-24.933)	(-20.739)	(-24.914)
Firm Effect		Controlled	Controlled	Controlled	Controlled	Controlled
Time Effect		Controlled	Controlled	Controlled	Controlled	Controlled
Regional Effect		Controlled	Controlled	Controlled	Controlled	Controlled
Industry Effect		Controlled	Controlled	Controlled	Controlled	Controlled
N	9481	9467	9467	9467	7666	9467
R^2		0.9151	0.0894	0.9152	0.9296	0.9151
adj. R^2		0.9040	−0.0305	0.9041	0.9182	0.9039

Note: t-statistic values are in parentheses.*$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

firms. This may be because private firms have more incentives to optimize their human capital structure compared to state-owned firms.

Columns (5) and (6) consider the differences in the characteristics of the regional business environment where enterprises are located. Note that an excellent business environment need not be completely consistent with the level of regional GDP. We follow the Research Report on China's Provincial Business Environment 2020 to classify the regional business environment. Specifically, regions with a total score of the business environment index above (H-market) and below (L-market) the median are and are not considered to be up to the business environment standard, respectively. The results indicate that the estimated coefficient of digital empowerment is significantly positive in both H-market (0.0792, $p < 0.05$) and L-market (0.4591, $p < 0.1$). This seems to prove that Enterprises with poorer business environments are more willing to enhance their human capital through digital reforms, thereby compensating for the inconvenience and disadvantages brought by the business environment.

4.6. Underlying mechanisms

Next, we use the mediating effects model to test the underlying mechanisms through which digital empowerment affects human capital. Table 6 reports the relevant regression results for different mechanisms, while Table 7 reports the results for the action channel test with Bootstrap sampling with 1000 repetitions. There is pair of columns for each mechanism in Table 6 as the stepwise regression method was used to test the mediating effect. Specifically, we first include the relevant mechanism as the explained variable (first column) and then as an explanatory variable (second column).

Columns (1) and (2) in Table 6 report the results for total factor productivity as the mediating mechanism. The estimated coefficient of digital empowerment on total factor productivity in column (1) is significantly positive ($p < 0.01$), while that of total factor productivity on labor employment in column (2) is significantly positive ($p < 0.01$). Thus, digital empowerment promotes total factor productivity, which in turn positively affects labor hiring. Hence, hypothesis H2c is supported.

Columns (3) and (4) in Table 6 reports the results for economies of scale as a mediating mechanism. The estimated coefficient of digital empowerment on economies of scale in column (3) is significantly positive ($p < 0.01$), while that of economies of scale on labor

Table 5
Heterogeneity test regression results.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	H–HHI	L-HHI	State	N-State	H-Market	L-Market
DT	0.1366*	0.0815**	0.0588	0.0864***	0.0792**	0.4591*
	(1.826)	(2.330)	(0.798)	(2.590)	(2.423)	(1.717)
Scale	0.6836***	0.6843***	0.6321***	0.6783***	0.6961***	0.5961***
	(20.032)	(32.430)	(11.209)	(36.727)	(36.252)	(14.520)
ROE	−0.3638***	−0.1417	−0.2709	−0.2262***	−0.2706***	−0.1300
	(-2.808)	(-1.608)	(-1.484)	(-2.968)	(-3.521)	(-0.587)
AGE	0.2845***	0.1132	0.3229	0.1420**	0.1295**	0.4491**
	(2.971)	(1.626)	(1.008)	(2.505)	(2.242)	(2.236)
RDS	0.0065**	0.0044**	0.0023	0.0046**	0.0043**	0.0057
	(2.365)	(2.083)	(0.504)	(2.470)	(2.259)	(1.596)
ROA	−0.0375	0.0526	0.0286	0.0503	−0.0035	0.0561
	(-0.398)	(0.764)	(0.132)	(0.855)	(-0.060)	(0.335)
CIR	−0.0721***	−0.0767***	−0.0722***	−0.0744***	−0.0779***	−0.0698***
	(-5.080)	(-9.309)	(-3.071)	(-10.085)	(-10.073)	(-4.168)
TobinQ	0.0262***	0.0099*	−0.0628***	0.0169***	0.0155***	0.0046
	(2.631)	(1.789)	(-3.282)	(3.351)	(3.111)	(0.273)
Constant Term	−9.9328***	−9.4473***	−8.4633***	−9.4305***	−9.7433***	−8.3631***
	(-13.430)	(-20.356)	(-5.965)	(-23.491)	(-23.123)	(-9.128)
Firm Effect	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Time Effect	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Regional Effect	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Industry Effect	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
N	3306	6068	786	8642	8236	1228
R^2	0.9106	0.9219	0.9564	0.9126	0.9132	0.9272
adj. R^2	0.8969	0.9095	0.9390	0.9002	0.9017	0.9162

Note: t-statistic values are in parentheses.*p < 0.10, **p < 0.05, and ***p < 0.01.

Table 6
Regression results for testing underlying mechanisms.

	(1)	(2)	(3)	(4)	(5)	(6)
	opacf	lnhumans	Sales	lnhumans	Manage	lnhumans
DT	0.0857***	0.1323***	0.0641***	0.0879***	−0.0229***	0.1120***
	(2.751)	(4.241)	(4.004)	(2.707)	(-4.622)	(3.476)
Scale	0.1517***	0.7515***	0.9037***	0.6028***	−0.0192***	0.6984***
	(10.136)	(44.545)	(84.787)	(22.562)	(-8.833)	(39.157)
ROE	0.7552***	0.0805	0.1422***	−0.2735***	−0.1223***	−0.1624**
	(10.472)	(1.109)	(2.988)	(-3.756)	(-12.633)	(-2.173)
AGE	−0.0705*	0.1165**	0.1116***	0.1385**	−0.0059	0.1532***
	(-1.859)	(2.284)	(3.874)	(2.513)	(-0.927)	(2.806)
RDS	−0.0017	0.0034**	−0.0003	0.0042**	0.0005***	0.0038**
	(-1.616)	(2.211)	(-0.425)	(2.561)	(3.404)	(2.316)
ROA	−0.0388	−0.0049	0.2040***	−0.0054	−0.0358***	0.0415
	(-0.854)	(-0.095)	(5.890)	(-0.098)	(-5.060)	(0.753)
CIR	−0.1861***	−0.1615***	−0.2451***	−0.0556***	0.0196***	−0.0931***
	(-16.551)	(-13.432)	(-19.519)	(-6.451)	(15.011)	(-12.051)
TobinQ	0.0022	0.0154***	0.0141***	0.0132***	0.0021***	0.0127***
	(0.557)	(3.376)	(4.684)	(2.716)	(3.095)	(2.627)
opacf		−0.4520***				
		(-18.468)				
Sales				0.0886***		
				(3.807)		
Manage						0.8054***
						(7.171)
Constant Term	5.8577***	−6.8469***	1.5874***	−9.6355***	0.5780***	−9.9604***
	(18.101)	(-18.350)	(6.797)	(-24.955)	(12.160)	(-25.215)
Firm Effect	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Time Effect	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Regional Effect	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Industry Effect	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
N	9467	9467	9467	9467	9467	9467
R^2	0.8463	0.9244	0.9793	0.9152	0.8858	0.9158
adj. R^2	0.8261	0.9145	0.9766	0.9041	0.8708	0.9047

Note: t-statistic values are in parentheses.*p < 0.10, **p < 0.05, and ***p < 0.01.

Table 7
Results of the action channel test.

Item	Total Effect	BootLLCI	BootULCI	Mediating effect value	Direct Effect	Test Conclusion
Digital Empowerment ⇒ Managerial Efficiency ⇒ Labor Employment	0.0936***	0.020	0.059	0.0396*** (3.980)	0.1603*** (4.846)	Mediation Effect
Digital Empowerment ⇒ Economies Scale ⇒ Labor Employment	0.0936***	0.001	0.008	0.0043** (2.415)	0.1956*** (5.788)	Mediation Effect
Digital Empowerment ⇒ Total Factor Productivity ⇒ Labor Employment	0.0936***	−0.282	−0.190	−0.2361*** (−10.048)	0.4360*** (12.879)	Cover Effect

Note: t-statistic values are in parentheses.*$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. BootLLCI and BootULCI denote the lower and upper limits of the 95% interval for Bootstrap sampling, respectively.

employment in column (4) is significantly positive ($p < 0.01$). Thus, digital empowerment promotes economies of scale, which in turn positively affects labor hiring. Hence, hypothesis H2b is supported.

Columns (5) and (6) in Table 6 reports the results for managerial efficiency as a mediating mechanism. The estimated coefficient of digital empowerment on managerial efficiency in column (5) is significantly negative ($p < 0.01$), while that of corporate managerial efficiency on labor employment in column (6) is significantly positive ($p < 0.01$). Thus, digital empowerment inhibits managerial efficiency, which in turn positively affects labor hiring. Thus, hypothesis H2a is not supported.

Table 7 reports the test results of bootstrap sampling. After sampling 1000 times, the results show that 0 is not included in the 95% confidence interval. Hence, the mediating effects of managerial efficiency, economies scale, and total factor productivity all exist. The total effect is 0.0936. First, the direct and indirect effects of managerial efficiency are 0.0396 and 0.1603, respectively; thus, managerial efficiency plays a mediating role. Second, the direct and indirect effects of economies scale are 0.0043 and 0.1956, respectively; thus, economies of scale play a mediating role. Third, the direct and indirect effects of total factor productivity are −0.2361 and 0.4360, respectively; thus, total factor productivity plays a cover role.

5. Conclusion

Using data on a sample of 1055 A-share listed manufacturing firms from China's Shanghai and Shenzhen stock exchanges from 2011 to 2020, we examine the relationship between corporate digital empowerment and corporate labor hiring by a panel fixed-effects model. Furthermore, we investigate the underlying mechanisms and channels through which corporate digital empowerment affects labor employment. Our findings are outlined below.

First, digital empowerment can increase labor employment. After controlling for the firm, time, regional, and industry effects, a 1-unit increase in digital empowerment significantly increases human capital by 9.36%. In other words, digital empowerment drives companies to hire more highly skilled and trained workers [25,83]. However, digital empowerment cannot reduce the overall employment, this is contrary to some research [83,84]. The main reason for this difference may be that these authors used all listed companies in China as research samples, while our article focuses on manufacturing enterprises. Therefore, our study helps to enrich and refine the research on the impact of digital empowerment on employment.

Second, the effect of digital empowerment on labor employment is heterogenous. Digital empowerment improves hiring of non-state enterprises by 8.64%. Meanwhile, hiring under an oligopolistic market structure increases by 13.66%, but only by 8.15% under a competitive market structure. Finally, hiring by companies with a superior business environment improves by 7.92%, far less than 45.91% of firms with inferior business environment.

Third, digital empowerment can improve the human capital structure and optimize the quality of labor hired in enterprises. For example, firms may hire more innovators and better managers. This is similar to other research findings [22,23]. In the process of digital transformation of enterprises, the improvement of R&D investment and human capital as mediating effects can significantly enhance their overall competitiveness [85] and optimize industrial structure [86]. So, companies should not worry about the cost of increasing human capital, as the benefits are obviously greater.

Fourth, digital empowerment can improve human capital by increasing managerial efficiency and economies scale [87]. Besides production efficiency [84], our study found that managerial efficiency is also a mediating effect. With the advancement of digitization, business will become more complex and diverse, enterprises should not only improve production efficiency, but also comprehensively enhance the overall management efficiency.

6. Discussion

Our study found that digital empowerment can significantly enhance the human capital of China's manufacturing enterprises through managerial efficiency and economic scale. In addition, we know that the digital economy can also promote industrial structure upgrading [88], achieve scale economy effect [89], improve enterprise performance [90], and enhance comprehensive competitiveness [85]. Undoubtedly, the digital development of enterprises can enable China's manufacturing industry to achieve a dual improvement in scale and quality. Thus, we make the following recommendations.

First, firms should grasp the opportunities of digital empowerment and accelerate the pace of their own digital transformation. Specifically, firms should fully leverage the advantages of data resources, fully utilize their existing advantages, use digital technology to explore new business models, and build a business ecosystem conducive to data and talent circulation.

Second, firms should enhance their level of specialization and improve the skills of their labor force to adapt to the evolving digital economy and competitive environment. Furthermore, they should expand the value-added and technological thresholds in their value chains, and leverage the advantages of dataflow by improving the quality of workforce resources. Finally, firms should maintain employee satisfaction and loyalty, build a competitive workforce and resource barriers that are differentiated from competitors.

Third, government departments should actively improve the local business environment, promote the free flow of labor resources, increase investments in training and social security of labor resources, supervise corporate behavior, improve the data resources supervision and labor employment security systems, and enhance social and platform governance. This will help to enhance the industrial value chain of China's manufacturing industry and build a new advantage for China's industrial development. Furthermore, it can ease the friction between the digital development of enterprises and the lag in skill development of the labor force.

Last but not least, incentive policies have a significant driving effect on digital transformation [91]. However, the effectiveness of policy implementation will be influenced by regional and corporate heterogeneity, as well as the interactions between enterprises [89]. Therefore, both governments and enterprises should tailor their digital transformation strategies according to local conditions.

7. Limitations

This study has some limitations. First, the reports of listed companies are usually strict and complete, and missing values are more likely to occur randomly. On average, the proportion of missing values for each variable of our data is only about 1%, so we deleted the missing values. Although we believe that directly deleting missing data will not have an impact on the results, subsequent researchers can verify it or use data from a larger range of Asian or global countries for research. Second, the information disclosure of enterprise digitalization is relatively limited; hence, we may not have comprehensively covered firm digital empowerment indicator. Further studies should especially analyze the system logic of digital empowerment, expand it into the value generation during the process of data flow, and construct indexes of digital empowerment that consider data resources, digital technology, digital capital, and other aspects. Third, due to limited space, we mainly focus on the three mechanisms of total factor productivity, economies of scale, and management efficiency. Further studies can analyze other mediating mechanisms such as corporate governance, supply chain management, enterprise operation, and financing. Fourth, while we have not done this, future researchers can examine the role of digital platforms in the competitive strategy of enterprises. Whether self-built or developed by a third party, digital platforms can help enterprises fully leverage the effects of their own digital empowerment and create new jobs.

Data availability statement

The data that support the findings of this study was collected from the China Stock Market & Accounting Research Database (CSMAR), and stored at https://github.com/XiuzeZhou/A-share_data.

CRediT authorship contribution statement

Liping Qiu: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Visualization. **Yixue Duan:** Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yang Zhou:** Visualization, Resources, Data curation. **Feng Xu:** Investigation, Resources. **Hanyu Zheng:** Investigation, Validation. **Xin Cai:** Validation, Visualization. **Zhibin Jiang:** Supervision, Resources, Project administration, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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