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Article

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Digital innovation and manufacturing employment - based on the analysis of mediating and threshold effects

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ABSTRACT

'Profound changes unseen in a century' superimpose the complex background of weak global economic growth. Employment affects a country's economic development and social stability, and is an urgent issue that every country needs to solve. This study examines the impact of digital innovation on the absorption capacity of manufacturing jobs, using data from listed companies from 2011 to 2021. The mechanism test indicates that digital innovation fosters enterprise employment through three principal avenues: enhanced total factor productivity, alleviation of enterprise financing constraints, and expansion of the market size. A heterogeneity analysis indicates that the impact of digital innovation is more pronounced in low-technology firms, state-owned firms, and technology-intensive firms. Further analysis revealed that the level of enterprise digital innovation positively affects the employment of high-tech and medium-skilled labour, while having no significant impact on low-skilled labour. In addition, the impact of digital innovation on employment in manufacturing enterprises is not a simple linear relationship, but there is a double threshold effect. When the level of digital innovation reaches a certain threshold, the effect of promoting employment becomes more significant. This study enriches the literature on the impact of digital innovation on employment and provides a useful reference for local governments on how to alleviate employment pressures.

IMPACT STATEMENT

The paper draws on data from listed companies in China to examine the impact of digital innovation on employment in the manufacturing industry. It combines theoretical insights with empirical evidence, employing the two-way fixed-effect model and the threshold effect model to investigate this relationship. The paper contributes to the theoretical understanding of the impact of digital innovation on employment and has significant practical implications, offering a valuable reference point for policymakers seeking to address employment challenges.

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1. An examination of the background

As China's economic development progresses towards a stage of high-quality growth, the employment structure of various industries in China is undergoing significant changes, with the overall employment form facing considerable challenges (Liu et al., 2023).

In the context of the digital economy, the application of emerging technologies, including artificial intelligence, big data, the Internet of Things and blockchain, has had a significant impact on traditional innovation activities. This process, and the resulting effect of enhancing traditional innovation activities through the use of digital technology, can be defined as digital innovation (Nambisan, 2017). In comparison to traditional innovation activities, digital innovation brings together a greater number of innovative elements, has a broader scope of application and has a stronger radiation-driven effect. The topic of digital innovation has been the subject of considerable research interest.

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Nevertheless, a notable gap remains in the literature on the impact of digital innovation on employment. The relevant theoretical constructs have yet to be evaluated against empirical evidence. In recent years, the advent of digital technology has not only given rise to novel business models and services but has also brought about significant transformations in traditional organisational structures and innovation processes. These developments challenge the existing understanding of the information systems field, prompting scholars to reassess innovation management frameworks. The integration of platforms and technologies in a digital environment has been demonstrated to markedly enhance organisational innovation capacity and management efficiency. The topic of digital technological innovation has recently become a prominent area of research, encompassing a range of aspects from business strategy to social innovation. The conceptual framework of digital business strategy elucidates the manner in which enterprises may leverage advanced technologies to transform traditional business models and gain a competitive edge in the market (Bharadwaj et al., 2013). Technologies such as the Internet of Things (IoT) are redefining corporate strategies and value chains, demonstrating specific pathways through which companies enhance their competitiveness via digital technology (Porter & Heppelmann, 2014).

The role of digital technology in fostering social innovation and addressing global challenges is becoming increasingly significant, with its contributions to sustainable development receiving growing recognition (George et al., 2014). During the digital transformation process, significant alterations in organisational behaviours and structures highlight pivotal challenges and success factors (Vial, 2019). The pervasive use of digital platforms enables companies in emerging markets to surmount developmental impediments, attain global connectivity, and foster innovation (Nambisan et al., 2017).

Digital technology also significantly impacts consumer behaviour, particularly in the realms of e-commerce and online services (Huang & Rust, 2018). Data science and analytics have become central to gaining a competitive advantage (Provost & Fawcett, 2013), while the extensive application of artificial intelligence and machine learning is reshaping industry landscapes and creating entirely new business models (Agrawal et al., 2018). The development of cloud computing allows companies to deploy resources more flexibly, reduce costs, and enhance the scalability and accessibility of services (Marston et al., 2011). The business models of digital platforms are gradually shaping industry structures and driving the evolution of innovation ecosystems.

Furthermore, the significance of digital technology in fostering social innovation and confronting global challenges is becoming increasingly recognised (George et al., 2014). As the application of technology becomes more pervasive, ethical and social responsibility issues related to digital technology, particularly concerning privacy and fairness in artificial intelligence and big data applications, are receiving increased scrutiny (Martin, 2019).

The advent of digital technology has given rise to a plethora of derivative products with the potential to contribute to sustainable development. One such example is green finance, which has the capacity to facilitate investment in renewable energy and enhance power output. Moreover, technological progress can impact the accessibility and utilisation of land resources in the context of food production (Zhuang et al., 2022). Furthermore, the advancement of digital technology will facilitate innovation in environmentally-conscious industries and the protection of the natural environment. It will also provide insights for companies to initiate green innovation activities and construct digital green business ecosystems (Yin & Zhao, 2024b). Nevertheless, the impact of digital innovation on employment remains an under-researched area, thus requiring further exploration and investigation. A substantial body of research exists on the relationship between technological progress and the structure of employment. While technological progress has been a significant driver of innovation and development in business activities, it has also led to notable technological improvements in the workforce of firms. The contribution of high-skilled employees to firm performance is a positive one (Li et al., 2022).

In recent years, China has reinforced its policy orientation with regard to priority employment, augmented the support for enterprises with a view to stabilising and expanding employment opportunities, and introduced a series of policies with the objective of fostering the stable development of enterprises and creating new jobs. In light of these developments, the issue of stabilising employment and protecting people's livelihoods has assumed an urgent dimension. The manufacturing industry has historically demonstrated the most robust and enduring employment stability. Over the past decade, China's

manufacturing enterprises have been responsible for creating approximately 45 million jobs, thereby playing a significant role in maintaining employment stability. During the '14th Five-Year Plan' period, the dual focus on supporting labour-intensive manufacturing industries with strong absorptive capacity and developing skill-intensive manufacturing industries that contribute to high-quality employment represented a significant strategy for fully unleashing the employment-stabilising and employment-promoting potential of traditional manufacturing industries. In the context of the development of the digital economy and the impact of domestic and international uncertainties, digital innovation offers new avenues for enterprises to reduce internal control costs, enhance the efficiency of asset operations and investment decisions, and ultimately improve their total factor productivity. Nevertheless, digital innovation exerts an influence on the employment of manufacturing enterprises. It is pertinent to inquire as to whether digital innovation will have an impact on the employment structure of manufacturing enterprises. Furthermore, it is essential to determine the role that digital innovation plays in stabilising employment, safeguarding people's livelihoods, and realising China's strategic goal of high-quality development.

In the context of an economic downturn, the investigation of the influence of digital innovation on employment in manufacturing companies is a matter of urgency. Consequently, this study seeks to examine and explore the effects and mechanisms of digital innovation on manufacturing employment through the utilisation of panel data from listed manufacturing firms over the period from 2011 to 2021. This study makes a number of contributions to the existing literature. The present study makes two contributions to the existing literature. Firstly, it expands the research on the employment effects of digital innovation in manufacturing enterprises. Secondly, it differs from existing studies in that it uses micro data to explore the impact of the degree of enterprise digital innovation on the manufacturing industry's employment absorption capacity and structure. The research presented in this paper provides a valuable reference point for the formulation of policies aimed at enhancing the competitive advantage of digital strategies and mitigating employment pressures.

2. Literature review and theoretical analysis

2.1. Economic consequences of digital innovation

In the extant literature, the definitions of digital technology innovation vary according to the specific research topic under consideration. However, the majority of literature in this field espouses a unified definition, namely that digital innovation is the utilisation of digital technology as the underlying foundation for innovation in products, production processes, organisational structures and business models.

The accelerated evolution of digital technologies has had a profound impact on a range of disciplines across the globe. In order to achieve net-zero emissions and sustainable development goals, digital technologies are facilitating efficient resource utilisation and environmental protection through the implementation of digitally integrated lean green methodologies (Liu et al., 2024). Concurrently, the ascendance of the digital economy has exerted a considerable influence on the demand for labour in the corporate sector, particularly when green technology innovations are the conduit (Hao et al., 2023). In the public sector, the advent of digital innovation is shaped by a multitude of factors, including the demands of the citizenry and the electoral incentives of local politicians. The advent of digital technologies has brought about a transformation in the manner in which government services are delivered. For multinational corporations, digital technologies present new opportunities, but their impact on employment is heterogeneous across countries and regions, as it is influenced by local factors (Abbasabadi & Soleimani, 2021; Ballestar et al., 2021.; Cirillo et al., 2021). Furthermore, investment in digital technologies represents a significant catalyst for eco-innovation, particularly in the domain of artificial intelligence, which has the potential to propel firms towards eco-innovation. Within firms, the combined effect of digital technologies, innovation, and skills drives the reorganisation of production and innovation processes. Furthermore, these factors are critical to understanding the impact of digital technologies on productivity, employment, and inequality (Ciarli et al., 2021). The advent of digital technologies has had a significant effect on the evolution of business models,

offering new avenues for firms to navigate the challenges posed by digital paradoxes (Ancillai et al., 2023). It is of the utmost importance to recognise the positive impact that digital technological innovation has on the environmental, social and governance performance of firms, thereby facilitating their sustainable development. Furthermore, the construction of digital infrastructure will exert a cascading influence on the countries involved in the Belt and Road initiative, enhancing the quality of infrastructure in the surrounding areas while also fostering bilateral economic transactions and sustainable development (Abbas et al., 2024a, 2024b). The preceding points collectively indicate that digital technologies are a pivotal factor in innovation and sustainable development, offering new prospects and challenges for advancement across a range of domains.

2.2. A review of literature related to the impact of digital innovation on employment

To date, there is still an evident gap in research exploring the employment effects of digital technological innovation, and the pertinent theoretical issues have yet to be tested using empirical data. Nevertheless, research related to technological progress can provide theoretical support.

The classical school of economics, as exemplified by the work of economists such as Ricardo, posits that the impact of technological progress on employment is a 'double-edged sword.' Technological progress may, on the one hand, facilitate the creation of new employment opportunities, but on the other, it may also result in the emergence of structural unemployment. One school of thought posits that technological progress will directly lead to 'technological unemployment,' whereby the impact of technological progress on employment is mainly to eliminate the traditional labour force (Postel-Vinay, 2022). An alternative perspective posits that while technological advancement exerts a direct impact on the employment landscape, it also stimulates growth through alternative channels. Consequently, when considered in its totality and over an extended period, technological advancement can contribute to employment growth (Sakurai et al., 1997).

By the 1990s, research on the employment effects of technological progress had made significant advancements, incorporating empirical research and other social practice data for verification, in comparison to the purely theoretical derivations of the previous period. Consequently, a more comprehensive analytical framework was established, and the following two fundamental points of consensus were reached:

There are two paths through which technological progress affects employment: a direct creative destruction mechanism (Aghion & Howitt 1994) and an indirect employment compensation mechanics. These two mechanisms work simultaneously, and the net effect of technological progress on employment depends on the strength of the two mechanisms.

Technological progress in different factors adjusts society's demand for differently skilled labour, thus affecting the evolutionary trend of skill orientation, which has a key impact on the total quantity of employment as well as on the structure of employment.

Existing research on the impact of technological advances on employment covers a number of aspects, and in conjunction with the object and subject of this study, it focuses on the interpretation of the relevant literature on the impact of AI technology and digitisation on employment.

A substantial corpus of literature has emerged to support the study of AI on the scale of employment. The majority of this literature posits that the development of AI exerts a pronounced substitution effect on total employment, which in turn will elevate the overall unemployment rate. A comprehensive discussion of the substitution and creation effects reveals that the application of AI can enhance the automation of firms, enabling them to modularise work processes and use robots to perform routine tasks. Consequently, the development of AI will lead to a reduction in medium-skilled jobs, but at the same time, it will also render those with non-routine job skills more desirable. Additionally, the development of AI will create many new jobs, and an analysis using U.S. global online job openings at the organisational level since 2010 found that job openings related to AI are growing rapidly with the development of AI technology, and that firms faced with a large number of vacancies are also reducing their hiring for non-AI jobs (Acemoglu et al., 2022). Further research has found that the impact of AI on employment is also affected by the level of inflation. There is a complex non-linear relationship between AI and unemployment, and the specific relationship depends on the critical value of inflation; when a

certain critical value is reached, the inhibitory effect of AI on employment will be weakened (Nguyen & Vo, 2022). At low inflation levels, the accelerated use of AI alleviates employment pressure and reduces the unemployment rate (Mutascu, 2021). In the long run, the replacement effect of artificial intelligence on employment will peak, and with the expansion of digital technology, the unemployment rate will reach a maximum, and then begin to decline, the relationship between the two overall 'positive U-shaped' trend (Zhu et al., 2023).

The application of digital technology in manufacturing leads to the long-term effects of increased productivity and reduced labour force, but in the short term, firms have difficulty compensating for the reduced labour force (Zhou, 2020), creating an incomplete employment compensation effect. On the other hand, digitalisation has had an impact on the labour market (Wang & Chang, 2021). Digitisation-intensive occupations grew faster, while the level of routinisation was negatively correlated with changes in employment. The digitalisation of industries has increased the share of medium- and high-skilled labour employment, reduced the share of low-skilled labour employment, and optimised the skill structure of employment (Wang & Luo, 2024). However, the impact may vary across industries, regions, and firm sizes, and targeted policies are needed to facilitate digital transformation and ensure the competitiveness of labour in employment. Furthermore, the importance of the economic cycle for technological advances in influencing the labour market cannot be ignored (Yao & Xu, 2022). During economic downturns, substitution effects play a dominant role, leading to a more drastic structural transformation of employment. Therefore, a balance between economic efficiency and social equity needs to be found in the design of employment policies.

2.3. Mechanisms of action of digital innovation affecting manufacturing employment

The trajectory of digital innovation as an emergent phenomenon at the level of foundational technology can be elucidated from a multitude of perspectives. With regard to manufacturing firms, the mechanisms through which digital innovation affects employment include productivity, financing, and market size effects.

Digital innovation in the overall management of the enterprise can play a role in management empowerment, investment empowerment, operation empowerment, and labour empowerment, which can help the enterprise to improve management efficiency, reduce internal control costs, and improve the quality of investment decisions and asset operation efficiency, so as to promote the growth of the total factor productivity of the enterprise (Huang et al., 2023).

While digital innovation does not directly address the issue of firms' financing constraints, it has a series of economic consequences that can effectively enhance firms' financing capacity. Similarly, as with the traditional two-way promotion of technological innovation and industrial development, digital innovation also serves to promote the development of the digital economy. The advancement of the digital economy can mitigate information asymmetry among the securities market, banks, and enterprises, thereby enhancing the capacity of enterprises to secure financing in the financial market (Li et al., 2023). A reduction in information asymmetry has been identified as a contributing factor to financial dynamism, which in turn has been linked to increased regional economic growth and employment levels (Iorember et al., 2024). Moreover, the advent of the digital economy has the potential to streamline enterprise investment processes, diminish transaction expenses, and refine the distribution of resources, thereby optimising the efficacy and efficiency of capital deployment and financing within the business sector (Peng & Luxin, 2022).

As an emerging factor of production, digital resources differ from traditional factors in that they do not follow the law of diminishing margins. Instead, they exhibit the phenomenon of increasing margins. The dual effect of increasing marginal utility and decreasing marginal cost allows enterprises to expand their market scale further. It has been observed in the literature that the digital economy can effectively reduce market friction (Chen, 2020) and that there is a multiplier effect between the digital economy and mega-market size (Chen & Wang, 2021), both of which contribute to the expansion of market size.

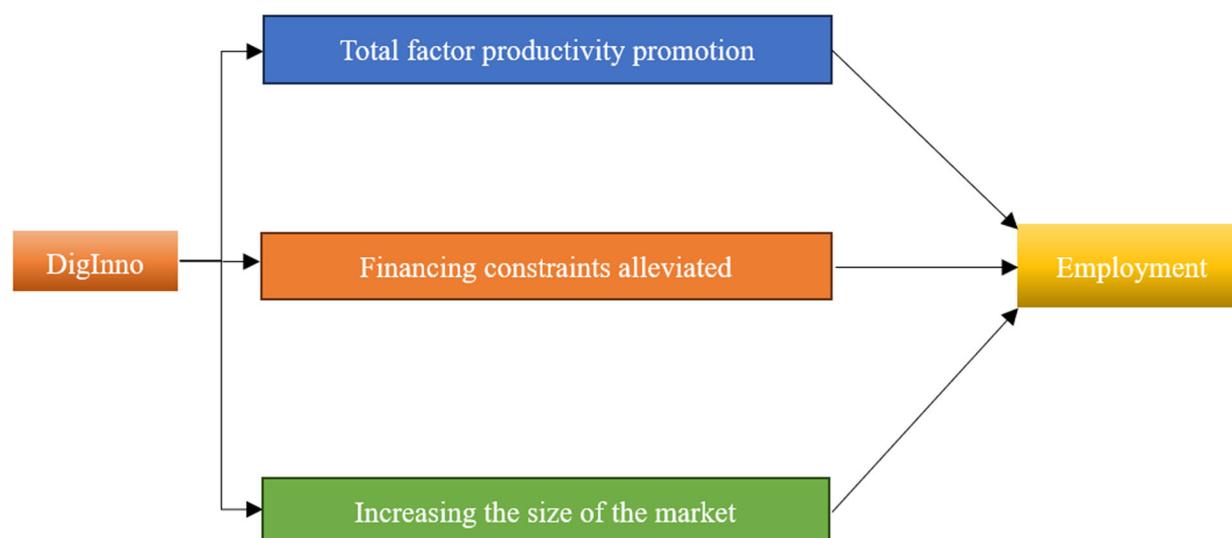


Figure 1. Mechanism of action diagrams.

Table 1. Hausman testing.

Test of H0: Difference in coefficients not systematic
$\chi^2(8) = (b-B)'[(V_b - V_B)^{-1}](b-B) = 5136.42$
Prob > $\chi^2 = 0.0000$
($V_b - V_B$ is not positive definite)

Combining the above analyses, this study proposes the core research hypothesis that digital innovation will promote employment in manufacturing firms through the productivity, financing constraint, and market size effects. The overall path diagram is presented in Figure 1.

3. Research and data methodology

3.1. Model testing approach

The research subjects of this paper are listed enterprises belonging to the manufacturing industry. It is acknowledged that micro individuals may exhibit unobservable heterogeneity across different enterprises, including factors such as management style, enterprise culture, technology level, and so forth. This unobserved heterogeneity may influence the impact of digital innovation on the employment level of enterprises. Consequently, it is proposed that individual fixed effects be incorporated into the regression analysis. The fixed effects model offers a means of effectively controlling for unobservable heterogeneity among individuals, thereby ensuring consistency and accuracy in the estimation results (Carbonell & Frijters, 2004).

In consideration of the data availability and research value, the study period selected in this paper is 2011–2021. During this period, there may be some common macroeconomic factors or policy changes, which will also have an impact on our study. The introduction of time-fixed effects facilitates the capture of common shocks and trends across different time periods, thereby enhancing the precision of the model estimation (Moon & Weidner, 2017). From a theoretical point of view, it is most scientific to choose a two-way fixed effects model for the study. But does this apply to the actual data, where the Hausman test is used to judge between fixed and random effects models?

The results of the Hausman test are shown in Table 1, where it can be seen that the P-value is 0.00 and the result is significant at 1% confidence level, therefore the original hypothesis is rejected, which means that there is a significant difference between the two approaches of fixed and random effects, and therefore it is more appropriate to choose the fixed effects model.

Accordingly, the two-way fixed effects model is selected as the primary model for this study. The econometric model was set up as follows:

$$\text{Employment}_{i,t} = \alpha_0 + \alpha_1 \text{Digilnno}_{i,t} + \beta X_{i,t} + \text{Year}_t + \text{Firm}_i + u_{it} \quad (1)$$

where subscripts i and t denote firms and time, respectively; $\text{Employment}_{i,t}$ represents firms' labour force size; $\text{Digilnno}_{i,t}$ represents firms' level of digital innovation; Year_t denotes year fixed effects; Firm_i denotes firms' individual fixed effects; and $u_{i,t}$ is a random perturbation term.

3.2. Variable definition

3.2.1. Explanatory variable

level of manufacturing labour employment, and the level of employment of differently skilled labour. The explanatory variable $\text{Employment}_{i,t}$ denotes firm employment and is expressed as the logarithm of the number of employees in listed company i in year t .

3.2.2. Core explanatory variables

The objective of this study was to ascertain the extent of digital innovation in manufacturing enterprises. A review of the existing literature reveals that the predominant method for assessing enterprise R&D innovation is through the quantification of patent applications. A number of studies have been conducted with the objective of identifying the key textual information of patents, distinguishing digital patents at the enterprise level from all applied patents, and using the number of digital patent applications as a measure of the level of digital innovation of enterprises (Liu et al., 2023).

The abstracts, specifications and claims of all invention and utility model patent application documents of listed companies were subjected to a keyword text analysis. Keywords pertaining to digital technologies were extracted from existing literature and government reports, and a textual analysis was subsequently employed to ascertain whether each patent was indeed a digital patent. The number of digital patents held by an enterprise in a given year was employed as an indicator of the enterprise's level of digital innovation in that year. This was achieved by adding 1 to the logarithm of the number of digital patents held, which was expressed as Digilnno (Huang et al., 2023). The digital technology keyword thesaurus is shown in Figure 2.

3.2.3. Control variable

In order to enhance the precision of the model estimation, this study selects the firm's year of establishment, the firm's financial leverage, the firm's size, the firm's board size, the firm's return on total assets, the firm's innovation intensity and the firm's growth as the control variables influencing the size of the workforce. The variables included in the model were selected based on their relevance to previous studies, thus enhancing the model's reliability (Li et al., 2024).

A review of the literature reveals that, in general, firms that have been in existence for a longer period of time tend to have a more stable market position and operational capacity, which in turn enables them to expand their workforce (Barba Navaretti et al. 2014). The influence of firms on employment opportunities is subject to variation at different stages of their life cycle. Mature firms typically possess

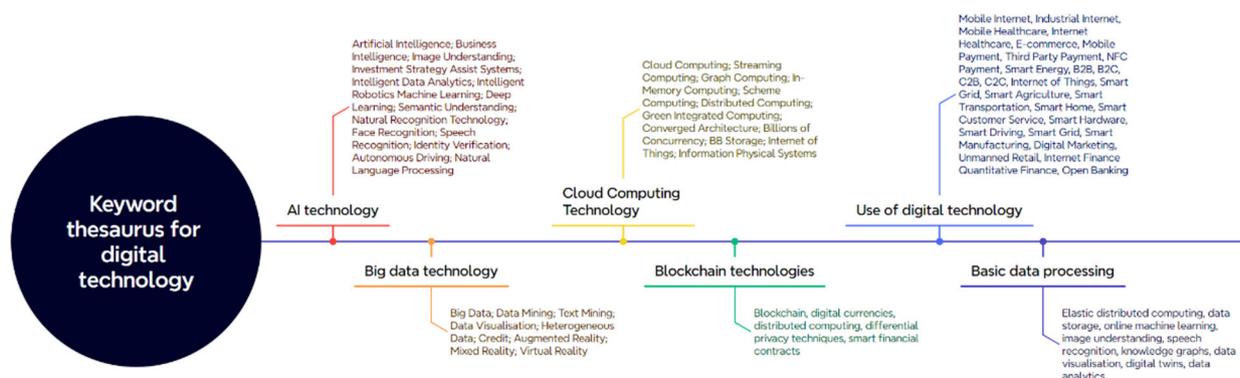


Figure 2. The digital technology keyword thesaurus.

Table 2. Description of main variables.

Variable type	variable symbol	variable name	Variable definition
explained variable	$Employment_{i,t}$	Size of labour	Natural logarithm of total enterprise labour force plus 1
explanatory variable	$Digilnno$	Digital Innovation	The number of digital patent applications filed by the enterprise within each year plus 1 to take natural logarithm
control variable	age	Age of business	Current year minus year of launch
	lev	financial leverage	Gearing ratio of the enterprise for the year
	$size$	Enterprise size	Total assets of the enterprise for the year
	$bsize$	Board size	Number of board members plus one takes the natural logarithm
	roa	Profitability	return on total assets
	$R\&D$	R&D investment	Ratio of R&D expenditure to operating revenue
	$Growth$	growth capacity	Revenue growth rate

greater resources and market competitiveness, enabling them to offer a greater number of employment opportunities.

A firm's financial leverage can exert a direct influence on the cost of employment, which can in turn give rise to fluctuations in the size of its workforce. However, this adverse effect is less pronounced for firms that have obtained B Corp certification (Paeleman et al., 2023). The size of an enterprise directly affects the scale and quality of its employment from a number of perspectives.

The impact of research and development (R&D) intensity on the scale of employment is a complex and multifaceted issue. The impact is mainly reflected in the following aspects: firstly, R&D investment can promote the development of new products and technologies, thus creating new employment opportunities; secondly, Furthermore, R&D activities can enhance the productivity and competitiveness of enterprises, thereby facilitating their expansion and fostering employment growth. Additionally, an increase in R&D intensity often results in an expansion of high-skilled employment opportunities and an enhancement of the overall quality of employment. Ultimately, an increase in R&D intensity typically leads to an expansion of high-skilled employment opportunities, thereby improving the overall quality of employment (Falk, 2012; Savrul & Incekara, 2015).

The influence of board size on employment levels is primarily evident in the realms of corporate governance, strategic decision-making, and risk management. Larger boards often offer a broader spectrum of expertise and knowledge, which can facilitate effective enterprise management and business expansion, thereby increasing employment opportunities. Furthermore, a diverse board of directors can enhance corporate social responsibility and employee welfare, which can contribute to employment stability and growth (Khanna & Palepu., 2004). Furthermore, the size of the firm, its return on investment and its growth affect the size of employment from a number of perspectives (Lever, 1996; Monteiro, 2019).

For the sake of convenience and clarity, the control variables will be presented subsequently in the text in abbreviated form including firm age (age), financial leverage (lev), firm size (size), board size (bsize), profitability (roa), R&D investment (Ratio of R&D expenditures to operating revenues), and growth rate (Growth annual growth rate of operating revenues), and the detailed variable data structure can be found in Table 2.

3.2.4. Data sources and processing

This study employs a sample comprising A-share listed companies in Shanghai and Shenzhen from 2011 to 2021 as the initial data set, which is then subjected to the following treatments: The initial sample was refined by excluding enterprises in other industries and retaining only those engaged in manufacturing. Secondly, the data of ST, *ST, PT, and other enterprises is deleted. Thirdly, observations with missing or abnormal key indicators are eliminated. Fourthly, the impact of outliers is reduced by trimming all micro-level continuous variables at the upper and lower 1% in order to control the impact of extreme values. Ultimately, 17,742 samples were obtained. The data regarding the fundamental characteristics of the enterprises, financial indicators, workforce size, and workforce structure were sourced from the Cathay Pacific database (CSMAR). The patent text data for the listed companies was sourced from the WinGo financial text data platform. The descriptive statistics of the main variables are presented in Table 3.

Table 3. Descriptive statistics of main variables.

Variable	Obs	Mean	Std, Dev	Min	Max
$Employment_{i,t}$	17742	7.732	1.125	4.644	12.571
<i>Digilnno</i>	17742	0.99	1.371	0	8.125
Age	17742	9.148179	6.769034	1	25
Lev	17742	.3931539	.1907187	.05391	.867631
Size	17742	22.04125	1.126472	20.0468	25.45853
Bsize	17742	2.228712	.1653331	1.791759	2.639057
Roa	17742	.0396452	.0733116	-1.395156	.7858651
$R\&D$	17742	4.405831	3.85808	0	22.52
Growth	17742	.2201379	.4885531	-.603122	2.81992

Table 4. Impact of digital innovation on the size of employment in manufacturing firms.

Variable	(1)	(2)	(3)	(4)
<i>Digilnno</i>	0.093*** (0.005)	0.085*** (0.005)	0.049*** (0.04)	0.025*** (0.03)
Age				-.031*** (0.001)
Lev				0.325*** (0.024)
Size				0.638*** (0.006)
Bsize				0.018 (0.024)
Roa				-0.088*** (0.038)
R&D				0.001*** (0.001)
Growth				0.002*** (0.001)
Firm fixed effect	No	Yes	No	Yes
Time fixed effect	No	No	Yes	Yes
N	17742	17742	17742	17742
R ²	0.058	0.059	0.008	0.634

3.3. Overview of data access

3.3.1. Overview of digital patent acquisition

There are two ways to obtain the number of digital patents, the first is to look up the data of digital patents of listed companies over the years directly through the China Research Data Service Platform (CNRDS), where there are data certified by authoritative organisations. However, this is not the way to obtain the data in this paper, because the data on digital patents in CNRDS is only opened to the public after the completion of the writing of this paper. The second way is to find the required patent information through the WinGo financial platform and then identify which are digital patents based on keywords.

3.3.2. Overview of how explanatory and other variables were obtained

The data were obtained from the authoritative database CSMAR. All the data required in the article can be found through the website guidelines. You can refer to the appendix placed at the end of the article for details on how to obtain it.

4. Benchmark results and robustness tests

4.1. Baseline estimated results

Table 4 reports the results of the baseline linear regressions of digital innovation affecting the employment size and employment structure of industrial firms. The results of regressions using panel regression, with firm fixed effects, time fixed effects, and control variables, respectively, from columns (1) to (4), demonstrate that despite the increasingly stringent research conditions, the impact of digital innovations on employment remains consistently positive and significant at the 1% confidence level. Furthermore, the estimated coefficient decreases from 0.093 to 0.025 as the research conditions are

tightened. This indicates that the enterprise fixed effects, year fixed effects, and the added control variables can absorb or weaken the impact of the original variables, thus improving the accuracy and reliability of the model.

Column (4) employs a time and individual firm bivariate stationary model for the baseline regression, with a range of relevant control variables. The estimated coefficient of firms' digital innovations (Digilnno) is 0.025 and remains significant at the 1% level, indicating that digital innovations significantly expand the size of the workforce of manufacturing firms, thereby enabling firms to provide more jobs. With regard to the control variables, the coefficients of firm size (size), financial leverage (lev), and firm growth (growth) are found to be significantly positive, indicating that the total value of a firm's assets and the growth rate of these assets contribute to its capacity for absorbing employment. The coefficients of enterprise age (age) and enterprise profitability (roa) are significantly negative, indicating that enterprises with longer years of establishment and high profitability may experience the phenomenon of capital and technology replacing labour in the process of digital innovation.

4.2. Robustness check

In order to guarantee the dependability of statistical inference, the model is capable of producing reasonable results even when faced with uncertainty or anomalies. Furthermore, in addition to enhancing the credibility of the statistical inference and guaranteeing that the model generates consistent and dependable outcomes in practical applications, a series of robustness tests were conducted based on the baseline regression model. These tests included replacing the core variables, measuring the level of digital innovation, and removing exogenous event shocks.

4.2.1. Replacement of core variables

In order to ascertain the frequency of specific keywords related to digital innovation in enterprise annual reports, a text analysis was conducted. This approach was first proposed by (Ding and Cheng, 2024). In order to gain insight into the connotations of digital innovation, policy texts containing keywords related to digital innovation and documents such as enterprise annual reports were collected. The frequency count of the occurrence of keywords related to digital innovation in the annual reports of enterprises was obtained through text mining and used to quantitatively analyse the digital innovation of enterprises, which is represented by Digilnno1. After replacing the measures of the core explanatory variables, the regression results are shown in Table 5, and their coefficients remain significant at the 1% confidence level.

Table 5. Measuring digital innovation using word frequency statistics.

Variable	(1)	(2)	(3)	(4)
Digilnno1	0.137*** (0.004)	0.137*** (0.004)	0.072*** (0.04)	0.017*** (0.035)
Age				−0.031*** (0.001)
Lev				−0.033*** (0.024)
Size				0.645*** (0.007)
Bsize				0.008 (0.024)
Roa				−0.088 (0.083)
R&D				0.039 (0.001)
Growth				0.002*** (0.001)
Firm fixed effect	No	Y	No	Y
Time fixed effect	No	No	Y	Y
N	17742	17742	17742	17742
R ²	0.02	0.02	0.003	0.634

Table 6. Replacement sample intervals.

Variable	(1)	(2)	(3)	(4)
Diginno	0.083*** (0.005)	0.073*** (0.005)	0.058*** (0.005)	0.023*** (0.003)
Age				-0.034*** (0.001)
Lev				0.318*** (0.024)
Size				0.64*** (0.007)
Bsize				0.029 (0.024)
Roa				-0.079** (0.037)
R&D				0.001* (0.001)
Growth				0.002*** (0.001)
Firm fixed effect	No	Y	No	Y
Time fixed effect	No	No	Y	Y
N	16810	16810	16810	16810
R ²	0.06	0.06	0.016	0.619

4.2.2. Replacement sample size

The preceding section presents a sample of listed manufacturing firms from 2011 to 2021. To demonstrate the robustness of the results, the sample interval is replaced with 2012 to 2021 and the sample is re-cleaned concurrently. During the aforementioned sample interval, there have been instances of new firms being successfully listed or existing firms being delisted. Consequently, the firms included in the sample have undergone changes following the replacement of the time interval. The results of the regression, according to the baseline model, are presented in Table 6, Replacement of Sample Size Test. As demonstrated in the table below, the coefficient estimates of the core explanatory variables are consistent with the baseline regression after modifying the sample interval. The level of digital innovation has the potential to enhance the employment scale of manufacturing enterprises as a whole, as well as the demand for high-skilled labour. Following the alteration of the sample interval, it was determined that digital innovation continues to exert a considerable influence on the demand for middle-skilled labour. However, the nature of this impact has undergone a shift when compared to the findings of the benchmark regression analysis. The global economy experienced a slowdown in 2012, particularly in major economies in Europe and the United States. Additionally, China reduced its economic growth target in 2012 to gradually align with the objectives of the Twelfth Five-Year Plan. This was done to direct all parties towards accelerating the transformation of the mode of economic development and to enhance the quality and efficiency of economic growth. A reduction in the economic growth target has had an effect on the employment of middle-skilled labour.

4.3. Endogeneity test

In econometric modelling, endogeneity typically denotes a correlation between specific variables and the error term. This correlation can result in biased parameter estimates and distorted statistical inferences. There are several principal reasons for endogeneity. The first of these is omitted variables, whereby variables of importance that are not included in the model may be correlated with those already included and thus affect some of the variables in the model. If these unobserved variables are correlated with the error term, then endogeneity occurs. In this study, micro-panel data of listed manufacturing firms is employed, and the quantitative variables of listed firms are not only of a complex nature but are also subject to undisclosed data. It is therefore unavoidable that econometric analyses will be affected by omitted variables, resulting in biased regression outcomes. (ii) Sample self-selection: Enterprises that are in a favourable position in terms of business conditions and/or have access to relevant policy support are more likely to engage in digital innovation activities and to have a higher level of digitisation. Consequently, there may be some sample self-selection issues. (iii) Bidirectional causality: the level of digital innovation will have an impact on the scale of hiring and hiring structure of

Table 7. Endogeneity test.

Variant	(1) Digilnno	(2) Employment _{i,t}	(3) Digilnno	(4) Employment _{i,t}
Digilnno		0.078*** (0.01)		0.376*** (0.091)
IV1: Digilnno_lag	0.867*** (0.007)			
IV2:dis			0.0001*** (0.0001)	
Firm fixed effect	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y
Control variable	Y	Y	Y	Y
N	17742	17742	17742	17742
Centered R ²		(0.699)		0.578

enterprises; at the same time, changes in the quantity and quality of employees will in turn act on the digital innovation process of enterprises, especially the number of high-level labour forces that may have a greater impact on the digital innovation of enterprises.

To mitigate the problem of endogeneity due to reverse causality and omitted variables, the lagged one-period instrumental variable for the level of digital innovation is introduced into the regression (Xie & Kuang, 2020). Column (4) controls for time and fixed effects, and the control variables in the baseline regression are added using two-stage least squares to identify endogeneity in the regression results. The results show that the sign and significance of the estimated coefficient results are consistent with those of the benchmark regression, proving that the results of this study are still significant after accounting for omitted variable endogeneity and two-way causality.

Self-media platforms, such as microblogging, can better reflect the close integration of regional economic development with the digital economy, while at the same time not having a direct impact on company employment. Based on the company's official website and microblog search, we used Python to crawl all enterprises that opened official microblogs from 2011 to 2021, and then matched them with city-level regional identifiers to calculate the number of enterprises that opened official city-level microblogs in that year (DIS) (Yang et al., 2023). We obtained a total of 3663 data sets from 333 prefecture-level administrative districts, which were used as the instrumental variable for digital innovation in the region.

The first stage instrumental variables result presented in columns (1) and (3) of Table 7 show that the estimated coefficients of both instrumental variables 1 and 2 are significantly positive at the 1 per cent level, fulfilling the hypothesis that the instrumental variables are correlated with the explanatory variables. Furthermore, the results of the second stage regressions in columns (2) and (4) show that the regression coefficient on the size of employment (Employment_{i,t}) is significant at the 1 per cent confidence level, suggesting that the main findings remain robust after accounting for potential endogeneity issues.

5. Further analysis

5.1. Analysis of impact mechanisms

According to the above analysis, it can be seen that the productivity enhancing effect of digital innovation plays an important role in enhancing the employment absorptive capacity of manufacturing enterprises. In this regard, the mediation test effects (2) and (3) are set based on the benchmark model (1).

$$Mediator_{i,t} = a_0 + a_1 Digilnno_{i,t} + \sum Controls + \sum Firm + \sum Year + u_{i,t} \quad (2)$$

$$Deployment_{i,t} = a_0 + a_1 Digilnno_{i,t} + a_2 Mediator_{i,t} + \sum Controls + \sum Firm + \sum Year + u_{i,t} \quad (3)$$

5.1.1. Productivity effect

Digital innovation in the overall management of a company can increase productivity by improving the standardisation of actual business processes, reducing the scope for manipulation and reducing the

internal and external control costs of running the company. This increases the capacity of a firm to absorb employment. According to economic theory, the increase in total factor productivity (TFP) is usually regarded as an important driving force for economic growth. As the TFP of manufacturing firms increases, they tend to adopt more advanced production technology, more efficient production processes and more optimised management methods. This improvement not only increases the productivity of the firm, but also increases output and output value. To meet increased demand, firms often need to increase labour inputs, including hiring more workers, technicians and managers. In addition, increased productivity improves competitiveness and profitability, which may encourage firms to expand their scale of production and market share. Expanding the scale of production usually requires an increase in the labour force, which contributes to an increase in employment opportunities.

In order to take into account, the variability between firms and to mitigate the endogeneity problem therein, the FE method is used to calculate the total factor productivity of manufacturing firms, which allows the model to control for invariant characteristics within a unit by introducing unit fixed effects variables. These invariant characteristics may include the unit's technological level, managerial ability and market position, which are usually related to productivity but may be correlated with other explanatory variables, leading to endogeneity problems. By controlling for these unit fixed effects, fixed effects models can minimise endogeneity problems and produce more reliable estimates.

5.1.2. Financing constraint effects

Digital innovation can have a multifaceted impact on the financing constraints of manufacturing firms. First, digital innovation brings new business models and growth opportunities that increase firms' profitability and market value, thereby improving their financing capacity. Second, digital innovation improves firms' business efficiency and risk management capabilities, reducing the risks and costs of financing. In addition, digital innovation can bring new financing channels and tools, such as decentralised financing based on blockchain technology, thus enriching firms' financing options. At the same time, digital innovation improves the level of information technology and data analysis capabilities of enterprises, improves information symmetry with investors and financial institutions, and reduces the uncertainty and costs of financing. Finally, digital innovation can also introduce new financing methods and tools, and provide more flexible financing options to meet the financing needs of firms at different stages and requirements.

The extent of financing constraints for manufacturing firms has important implications for employment. First, financing constraints limit the ability of firms to raise finance, leading to constrained investment plans, which in turn affect productive capacity and labour demand. Second, financial constraints can lead to a decline in productivity, limiting firms' market competitiveness and thus affecting employment growth. In addition, firms facing financial constraints may resort to measures such as layoffs and wage cuts to reduce costs, further affecting the employment and income levels of their workers.

The KZ Index was chosen as an indicator to measure the level of corporate financing constraints (Jiang et al., 2016). The KZ Index (Kaplan-Zingales Index), proposed by Kaplan and Zingales, is an index used to measure corporate financing constraints. This index is primarily used to measure the level of corporate financing constraints, that is, the ease with which a firm can access external financing.

$$KZIndex = \frac{Capital\ Expenditures}{Enterprise\ Value} \quad (4)$$

5.1.3. Market size effect

Based on the above theoretical analysis, digital innovation plays an important role in promoting employment in manufacturing enterprises, and expanding market scale is one of the key factors. Through the application of digital technology, manufacturing enterprises can explore new markets and achieve global sales, thereby increasing production demand and expanding market size. In addition, digital innovation also prompts enterprises to develop more competitive new products and services to meet the changing market demand, which in turn attracts more consumers and promotes the expansion of market size. The introduction of digital technology can also improve the operational efficiency and transparency of the market, reduce transaction costs, promote healthy competition, ensure the survival of the fittest, and

Table 8. Mechanism of action tests.

Variant	(1) TFP_FE	(2) Eployment _{i,t}	(3) KZ	(4) Eployment _{i,t}	(5) MS	(6) Eployment _{i,t}
DigilInno	0.012*** (0.003)		0.044*** (0.015)		0.015*** (0.003)	
TFP_FE		0.271*** (0.009)				
KZ				0.018*** (0.002)		
MS						0.346*** (0.008)
Firm fixed effect	Y	Y	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y	Y	Y
Control variable	Y	Y	Y	Y	Y	Y
R ²	0.846	0.659	0.192	0.664	0.863	0.679

provide more development opportunities for outstanding manufacturing enterprises. In addition, digital innovation creates new industrial ecosystems, integrates resources from all parties, and provides employment opportunities. Finally, digital innovation helps enterprises optimise their organisational structure, develop external markets, and promote scale expansion, thus enhancing their growth. Digital innovation is in line with the current trend of reform and transformation of Chinese enterprises, and capital is highly inclined towards such enterprises, further stimulating their growth momentum and vitality. Sustained growth will continue to attract high levels of technology and labour. Drawing on Ni Kekin (2021) methodology, the log Market Scale (MS) of the growth rate of corporate revenue is chosen as a measure of corporate scale to test how corporate digital innovation affects employment through scale effects.

The results of the mechanism test are shown in Table 8, and it is clear from the empirical results that digital innovation will promote the level of employment through the productivity effect, the financing constraint effect, and the market size effect.

5.2. Heterogeneity analysis

5.2.1. Differences in technology levels

Theoretical analysis suggests that the degree of digital innovation in firms at different stages of the technology level has different effects on labour force employment. This study refers to the statistical analysis method of quartiles, which is usually used to measure the difference in the technological level of enterprises. First, the total factor productivity of the sample data is sorted from smallest to largest, and enterprises with total factor productivity lower than the lower quartile are defined as low-technology level enterprises, and enterprises with total factor productivity higher than the upper quartile are defined as high-technology enterprises.

5.2.2. Differences in the nature of property rights

The nature of enterprises' property rights is different, and their development objectives and external constraints will also be quite different, so the heterogeneity test should be conducted on the nature of enterprises' property rights. Here, the sample data are divided into two categories, state-owned enterprises and non-state-owned enterprises, according to the nature of the enterprise property rights to be analysed separately.

According to the traditional perspective, privately owned enterprises focus on market competition and efficiency, tend to adjust their staffing flexibly to changes in market demand, and place more emphasis on a highly skilled, high-level workforce. In contrast, state-owned enterprises, which are controlled or influenced by the government, pay more attention to social responsibility and stable employment, and their staffing and job creation may be restricted by policies favouring the provision of stable income and benefits. Together, factors such as government policies, enterprise business philosophy, and the competitive market environment influence the labour demand and recruitment strategies of both types of enterprises.

However, with the acceleration of digital transformation, demand for digital talent in state-owned enterprises has gradually increased. There are several reasons behind this change. First, the government has introduced policy measures to support SOEs in accelerating digital transformation, encouraging them to invest in digital transformation and create more digital innovation jobs. Second, with the booming digital economy, the market demand for digital products and services is growing, prompting SOEs to increase their investment in digital transformation. Finally, technological advances have driven the application of digital technologies in various industries. Consequently, the increased demand for talent for digital innovation in SOEs has become a new trend, and companies are likely to increase their efforts to cultivate and recruit digital talent to meet the needs of digital transformation.

5.2.3. Differences in the structure of factor inputs

According to Yang Ligao (2018) method of classifying the three major types of industries in the manufacturing industry, listed companies in the manufacturing industry as a whole are classified into three major types: labour-, capital-, and technology-intensive.

Labour-intensive enterprises use human labour as the main production factor and usually rely more on manual operations and manual labour; capital-intensive enterprises rely mainly on large capital investment and high-cost capital equipment, such as mechanised production lines; and technology-intensive enterprises focus on technological innovation and high-end technology application, relying on a high level of technical talent and R&D capabilities. There may be differences in the impact of digital innovation on employment in these three types of firms. For labour-intensive firms, digital innovation may contribute to employment growth as digital technology improves production and management efficiency and expands the scale of production; however, for capital-intensive firms, the impact of digital innovation on employment is likely to be less significant because it relies mainly on capital equipment and technological inputs, rather than labour resources. For technology-intensive firms, digital innovation may have a positive employment impact because of its focus on technological innovation and high-end technology applications, and digital technologies help to promote innovative activities and increase the demand for highly skilled personnel.

The results of heterogeneity tests are presented in Table 9. Columns (1)–(2) show the results of the analysis of the impact of digital innovation on employment in manufacturing enterprises of different technological levels, showing that whether it is a high technology level or a low technology level, digital innovation can significantly promote the employment situation of the enterprise, but the promotion effect of digital innovation on employment is more obvious in enterprises with a low technological level, which may be due to the fact that enterprises with a high technological level have a certain amount of talent reserves. When enterprises face the demand for digital innovation, they can quickly use the

Table 9. Heterogeneity test.

Variant	Differences in technology levels		Differences in the nature of property rights		Differences in the structure of factor inputs		
	High level	Low level	State Holding	Non-municipal	Labor-intensive	Technology-intensive	Capital-intensive
DigInno	0.022*** (0.005)	0.036*** (0.006)	0.013** (0.006)	0.031*** (0.004)	0.016** (0.007)	0.027*** (0.004)	0.003 (0.019)
Age	-0.03*** (0.002)	-0.029*** (0.002)	-0.036*** (0.002)	-0.027*** (0.002)	-0.031*** (0.002)	-0.028*** (0.002)	-0.039*** (0.004)
Lev	0.157*** (0.05)	0.471*** (0.037)	0.291*** (0.043)	0.308*** (0.029)	0.294*** (0.045)	0.357*** (0.031)	0.146* (0.075)
Size	0.652*** (0.012)	0.558*** (0.012)	0.639*** (0.011)	0.632*** (0.008)	0.641*** (0.012)	0.655*** (0.008)	0.565*** (0.023)
Bsize	0.074* (0.038)	0.078** (0.038)	0.035 (0.041)	0.006 (0.029)	-0.034 (0.044)	0.057* (0.03)	-0.145** (0.069)
Roa	-0.17** (0.079)	0.028 (0.052)	-0.261*** (0.074)	0.006 (0.043)	-0.285*** (0.075)	0.028 (0.045)	0.101 (0.131)
R&D	0.01*** (0.003)	0.001 (0.001)	0.002 (0.001)	0.001 (0.001)	0.005* (0.003)	0.001 (0.001)	-0.005 (0.007)
Growth	0.001*** (0.003)	-0.01*** (0.004)	0.002 (0.002)	0.003*** (0.001)	-0.005 (0.004)	0.003*** (0.001)	-0.027*** (0.009)
N	5332	7090	5482	12845	5405	10403	1931
R ²	0.508	0.221	0.659	0.602	0.681	0.655	0.507

existing talent to complete the corresponding innovation work, while the original low-tech human resource level is lower, so it will absorb more labour.

Columns (3) to (4) show the empirical results in manufacturing enterprises with different property rights, and their regression coefficients are significant, but the sample coefficients of non-state-owned enterprises are relatively large, which is due to the fact that the two types of enterprises in the business objectives, recruitment forms and types of employee management there is a big difference between the two types of enterprises, and the state-owned enterprises have more stability in their employees, and the recruitment of employees should take into account the requirements of various aspects, such as Relieve employment pressure, conform to the macroeconomic cycle and other factors. The recruitment form of non-state-owned enterprises is more flexible, so they can respond quickly to the demand for talent in technological progress.

Columns (5)–(7) show the empirical results for enterprises with different factor structures. The impact of digital innovation on employment is significant in both labour- and technology-intensive enterprises, while the results are not significant in capital-intensive enterprises. Capital-intensive enterprises are mainly heavy industries such as the metallurgical and machinery manufacturing industries, which are characterised by many technical equipment, large capital investment, and less labour force; thus, the impact of digital innovation on employment in this type of enterprise is not significant. Among labour- and technology-intensive enterprises, the employment effect of digital innovation on the latter is stronger, which is also in line with the relevant laws of economics.

5.3. Impact on the structure of the labour force

The empirical results in the previous section indicate that among listed manufacturing enterprises, digital innovation significantly increases enterprises' ability to absorb labour and alleviate employment pressure. In the process of promoting economic development and alleviating employment pressure, the impact of digital innovation on the labour force structure is also a question worth exploring. Referring to Yuan Dongmei (2021) approach, based on the baseline regression model, the dependent variable is classified into a high-end high-skilled labour force, middle-end high-skilled labour force, middle-skilled labour force, and low-skilled labour force according to the level of education (Yuan et al., 2021).

As can be seen in Table 10, digital innovation does not have the same impact on the labour force for different skill structures. In terms of the degree of significance, the impact of digital innovation on the employment of high-end high-skilled, mid-range high-skilled, and middle-skilled labour force is positively correlated at the 1% confidence level, but the impact on the low-skilled labour force is not significant, because the low-skilled labour force is more mobile and will be affected by more external factors than the other three types of labour force. In terms of the degree of impact, digital innovation has the most obvious stimulating effect on the employment of mid-range high-skilled labour, which is malleable and

Table 10. Impact of digital innovation on different labour force employment structures.

Variant	(1) High-end, high-skill	(2) Highly skilled mid-range	(3) Intermediate skill	(4) Low-skilled
DigilInno	24.53*** (3.803)	113.57*** (11.66)	45.79*** (13.27)	-7.62 (8.97)
Age	-0.468 (1.425)	12.66*** (4.37)	9.47* (4.97)	-97.11*** (3.36)
Lev	-149.64*** (26.21)	-465.92*** (80.38)	-346.59*** (91.49)	107.26* (61.83)
Size	139.18*** (7.02)	672.59*** (21.52)	685.94*** (24.49)	143.93*** (16.552)
Bsize	-53.21** (26.14)	-50.11 (80.15)	47.31 (91.23)	-62.4 (61.66)
Roa	-91.37** (41.26)	-377.39*** (126.54)	-392.39*** (144.02)	-151.72 (97.33)
R&D	4.17*** (0.93)	12.45*** (2.84)	-3.13 (3.23)	1.28 (2.18)
Growth	-0.41 (0.65)	0.65 (1.98)	1.19 (2.26)	-0.09 (1.53)
N	17742	17742	17742	17742
R ²	0.124	0.339	0.291	0.001

downward compatible, and the proportion of the labour market is not short of increasing; when enterprises need to complete more innovative tasks, they will increase their demand.

5.4. Threshold characteristics of the impact of digital innovation on employment

The creative and destructive effects of technological progress have been elaborated in detail in the previous section, but the relationship between the strengths and weaknesses of these two effects is in a dynamic process of change, so the impact of the level of digital innovation on employment should theoretically be a non-linear relationship.

Based on the threshold characteristics regression model proposed by Hansen (1999), the non-linear econometric model of digital innovation and employment is set as:

$$\text{Employment}_{i,t} = \beta_0 + \beta_1 \times \text{DigilInno}_{i,t}(\mathbf{q}_{i,t} \leq \lambda_1) + \beta_2 \times \text{DigilInno}_{i,t}(\lambda_1 < \mathbf{q}_{i,t} \leq \lambda_2) + \beta_3 \times \text{DigilInno}_{i,t}(\lambda_2 < \mathbf{q}_{i,t}) + \alpha Z_{i,t} + \mu_i + \varepsilon_{i,t} \quad (5)$$

Considering that the research sample size of this paper is large and belongs to unbalanced panel data, referring to the practice of Wang (2015), brutal bootstrap sampling is used for unbalanced panel data to confirm the threshold value, and the results of threshold effect test are obtained as follows:

Table 11 Shown are significance tests, threshold estimates and confidence intervals for the threshold of digital innovation on employment in manufacturing firms, analysing the double-threshold effect according to the principle of treating the issue from complexity to simplicity.

Figure 3 is a plot of the likelihood ratio as a function of the double threshold, where the solid line is the likelihood ratio of the threshold variable and the dashed line is the critical value (7.53) at the 5% significance level.

Table 11. Threshold effect test and threshold estimation results.

	F	P	10%	5%	1%	Threshold Value
Single	76.03***	0.000	8.54	10.25	14.81	3.045
Double	16.15***	0.002	7.23	9.08	12.81	1.386
						3.178

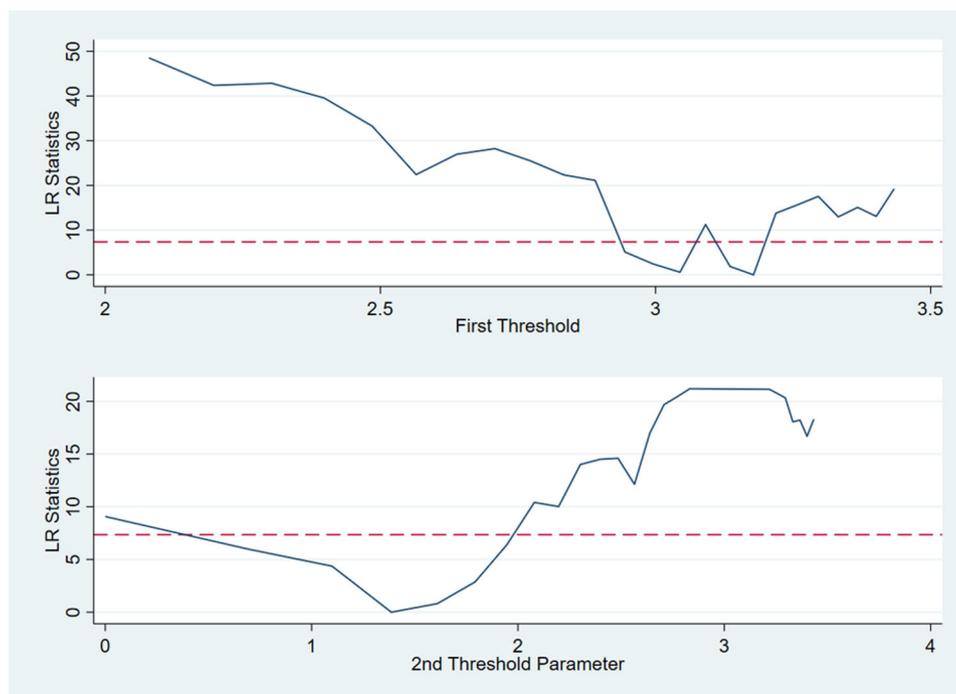


Figure 3. Estimated threshold.

Table 12. Estimation of threshold regression coefficients.

Variable	Coefficient Estimate	Standard Deviation	t
Digilnno.a	0.008	0.007	1.15
Digilnno.b	0.023***	0.006	3.59
Digilnno.c	0.045***	0.006	6.51
age	0.037	0.001	26.23
lev	1.039***	0.045	23.19
bsize	0.315***	0.038	8.2
roa	0.525***	0.064	0.84
R&D	0.001	0.002	0.84
Growth	0.005***	0.001	6.45
N = 17742		R ² =0.395	

Table 12 shows the results of the analysis of the two-threshold regression model. Through the unbalanced panel threshold regression model test, it is found that the impact of the level of digital innovation on the employment of manufacturing enterprises has a 'double threshold effect', and the relationship between the two is non-linear. At a low level of digital innovation ($\text{Digilnno} \leq 1.386$), the impact of digital innovation on employment is not significant, because digital innovation at this stage is still mainly in the theoretical innovation stage, with less impact on reality. When digital innovation is at a medium level ($1.384 < \text{Digilnno} \leq 3.178$), the estimated coefficient of digital innovation on manufacturing employment is 0.023, which can be seen that when the digital technology is carried out to a certain level, the digital innovation plays a role in promoting employment, which is in line with the conclusion of the previous article. When digital innovation breaks through the second threshold ($\text{Digilnno} > 3.178$), the estimated coefficient rises to 0.045, indicating that with the development of digital innovation, the employment stabilising effect of digital innovation gradually increases.

6. Research findings and policy recommendations

6.1. Discussion

In the context of global economic growth that is characterised by a general sense of stagnation, the question of how to alleviate the pressures facing the employment market has become a matter of urgency for all economies. The digital economy represents a novel economic paradigm that is fundamentally distinct from the traditional industrial economy. It has the potential to significantly reduce social transaction costs and enhance the efficiency of resource optimisation and allocation. Nevertheless, it is evident that the extant literature on the influence of digital innovation on employment is still incomplete. At this juncture, the predominant focus is on the impact of digital innovation on job creation and substitution. However, it is imperative to investigate whether this will exacerbate the anxiety surrounding unemployment and the potential implications of smart applications. These are pressing issues that require further rigorous investigation and discourse.

This study examines the impact of digital technology on employment issues in the manufacturing industry. It demonstrates that the development of digital technology has not only benefitted the manufacturing industry in numerous ways but has also had a significant and far-reaching impact on a vast array of other industries. To illustrate, COVID-19 had a severe impact on the tourism industry, which was severely disrupted. However, the advent of digital technology has enabled the tourism industry in some areas to implement measures to mitigate the effects of the epidemic. These include the use of digital technology to streamline the sale of tour groups and customer registration, enhance risk monitoring capabilities, provide enhanced protection for tourists, and improve the overall service quality of the tourism industry (Abbas et al., 2021). Furthermore, the topic of digital innovation and its impact on the quality of employment warrants further investigation. In addition to the enhanced skill requirements for newly recruited employees, digital innovation can facilitate the transformation of human resource management in firms. The digitisation of human resources has been shown to enhance creativity. The digital transformation of HRM has the potential to enhance employee creativity, either directly or indirectly through self-efficacy, thereby improving the quality of HR in organisations (Abbas et al., 2023a, 2023b). The advancement of digital technology can also facilitate innovation in other domains, including green

innovation, the environmentally conscious development of diverse business operations, and the establishment of enterprises that prioritise environmental optimisation. The integration of digital green innovation practices can significantly bolster the competitive edge of enterprises (Yin et al., 2024). Furthermore, the advancement of digital technology in the financial sector has the potential to enhance the financial performance of enterprises (Abbas et al., 2024a, 2024b). As the most influential area of technology, digital technology has attracted a great deal of attention and research worldwide. This technology is changing the world at an alarming rate, and both people's lifestyles and economic activities have been affected by this technology. In future scientific research, digital technology will continue to play a very important role, for example, in the field of environmental protection, the traditional building materials industry to the transformation of green intelligent building materials industry depends on the progress of digital technology, which will help reduce carbon emissions and promote sustainable development (Yin & Zhao, 2024).

This paper addresses two key questions: firstly, whether digital innovation affects the size of employment in manufacturing firms; and secondly, what are the potential ways in which digital innovation affects the size of employment. The investigation of these two issues through in-depth research and discussion is of great theoretical and practical significance. From a theoretical standpoint, this research represents a significant contribution to the existing literature on this topic. From a practical standpoint, it offers novel insights into the formulation of government employment policies in the context of subdued global economic growth.

6.2. Conclusion

This study uses data from China's Shanghai and Shenzhen A-share listed manufacturing enterprises from 2011 to 2021 as the initial sample, portrays the degree of digital innovation of enterprises with the help of text analysis, and adopts a two-way fixed effects model to explore the impact of digital innovation on the employment scale and employment structure of manufacturing enterprises in depth. The relevant conclusions are as follows. First, digital innovation, as a new strategic organisational form leading to a new round of technological and industrial revolution, significantly contributes to the expansion of employment scale and optimisation of employment structure in manufacturing enterprises, and this conclusion still holds after a series of robustness tests. Second, digital innovation can improve the total factor productivity of enterprises, alleviate their financing constraints, expand their market scale, and further increase their labour demand through a combination of the financing, the total factor productivity effect, and scale effects. Thirdly, there is heterogeneity in the labour-employment effect of digital innovation in enterprises with different property rights, factor input structures, and technology levels. The impact of digital innovation on the employment scale and structure of manufacturing enterprises is more conducive to increasing the labour demand of high-tech, labour-intensive, state-owned enterprises. Finally, following a threshold analysis, it was determined that the impact of digital innovation on the employment size of manufacturing firms is not a straightforward linear relationship. Instead, a notable threshold effect was observed between the two variables. It was found that digital innovation has a significant promotion effect on the employment scale of manufacturing enterprises only when a certain threshold is reached. Furthermore, this promotion effect is more effective when the level of digital innovation surpasses a certain threshold.

6.3. Managerial implication

For manufacturing enterprises, digital innovation can significantly improve their various business indicators, which in turn expands their labour demand and alleviates social employment pressure. Enterprises should comply with the development trend of digital economy, enhance the R&D investment in digital innovation, improve the basic R&D capability, and at the same time pay attention to the new technology application scenarios required by the digital economy. The key for manufacturing enterprises to enhance their digital innovation level is to formulate a clear digital strategy and strengthen digital infrastructure. The introduction of advanced digital technologies, such as the Internet of Things, big data analytics, and artificial intelligence, can optimise product design, production processes, and supply chain management

and improve the productivity and product quality of enterprises. Additionally, strengthening talent training and updating technologies is essential. Companies should focus on digital skills training for their employees and constantly monitor the latest technologies and trends in the industry. Promoting organisational culture transformation, creating an atmosphere that supports digital innovation, strengthening cooperation with the digital ecosystem, and establishing a mechanism for continuous improvement are all key measures for promoting digital innovation in manufacturing enterprises. These initiatives help enhance the digital capabilities and competitiveness of enterprises and achieve sustainable development.

6.4. Social implications

Digital innovation increases enterprises' demand for high-skilled labour. We should continue to increase support for higher education, especially postgraduate education, while accelerating plans to cultivate digital talents, improve the system for cultivating digital talents in colleges and universities; strengthen collaboration between industry, universities and research institutes to cultivate digital talents; accelerate vocational training in digital skills; and increase the incentives for digital talents to motivate the entry of more talents from related disciplines, in order to further enhance the level of digital economy and the degree of digital innovation.

The impact of digital innovation on the employment of high-tech enterprises and state-owned enterprises has become more evident. While digital innovation affects the employment level of enterprises through various mechanisms, it also reflects different degrees of improvement in the operational efficiency and management level of different types of enterprises, which may continue to widen the 'digital divide' in the future. Therefore, the Government can implement several policy measures. First, the government can increase its support for low-skilled enterprises and private enterprises and help them upgrade their digitisation level and improve their competitiveness by providing financial subsidies, tax incentives, and technical training. Second, the Government can enhance the popularisation and promotion of digital technology by strengthening education on digital technology, building digital infrastructure, and promoting the application of digital technology in various industries. Additionally, the government can formulate relevant policies and regulations to encourage enterprises to strengthen cooperation and sharing, promote the sharing and innovation of digital technologies, and facilitate the collaborative development of industries. Through these policy measures, the government can effectively prevent further widening of the digital divide, encourage various types of enterprises to work together to realise digital transformation, and promote sustainable economic and social development.

Authors' contribution

Jianjiang Liu - Selection of themes and discussion of feasibility. Provide writing ideas and write article outlines. Approval of upcoming releases. Conceptualisation and design of the paper;5. Interpretation of data

Qi Tang - Selection of themes and discussion of feasibility. Finding and organising data. Conducting empirical tests as well as writing the main body of the article. Interpretation of data

Fidelis Ayangbah - Critically revised the intellectual content of the paper. Translating articles into English, controlling the final formatting. The discussion of article writing ideas makes very important suggestions. Conceptualisation and design of the paper.

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Data availability statement

Data will be made available on request.

References

- Abbasabadi, H. M., & Soleimani, M. (2021). Examining the effects of digital technology expansion on Unemployment: A cross-sectional investigation. *Technology in Society*, 64, 101495. <https://doi.org/10.1016/j.techsoc.2020.101495>
- Abbas, M., Al-Sulaiti, K., Al-Sulaiti, I., & Abbas, J. (2023a). Innovation, self-efficacy and creativity-oriented HRM: What helps to enhance the innovativeness of organization employees? *Journal of Personnel Management*, 1, 54–67. <https://journals.smarcons.com/index.php/jpm/article/view/198>
- Abbas, J., Balsalobre-Lorente, D., Amjid, M. A., Al Sulaiti, K., Al Sulaiti, I., & Aldereai, O. (2024a). Financial innovation and digitalization promote business growth: The interplay of green technology innovation, product market competition and firm performance. *Innovation and Green Development*, 3(1), 100111. <https://doi.org/10.1016/j.igd.2023.100111>
- Abbas, J., Mamirkulova, G., Al-Sulaiti, I., Al-Sulaiti, K. I., & Dar, I. B. (2024b). Mega-infrastructure development, tourism sustainability and quality of life assessment at world heritage sites: catering to COVID-19 challenges. *Kybernetes*, (ahead-of-print). <https://doi.org/10.1108/K-07-2023-1345>
- Abbas, J., Mubeen, R., Iorember, P. T., Raza, S., & Mamirkulova, G. (2021). Exploring the impact of COVID-19 on tourism: Transformational potential and implications for a sustainable recovery of the travel and leisure industry. *Current Research in Behavioral Sciences*, 2, 100033. <https://doi.org/10.1016/j.crbeha.2021.100033>
- Abbas, J., Wang, L., Ben Belgacem, S., Pawar, P. S., Najam, H., & Abbas, J. (2023b). Investment in renewable energy and electricity output: Role of green finance, environmental tax, and geopolitical risk: Empirical evidence from China. *Energy*, 269, 126683. <https://doi.org/10.1016/j.energy.2023.126683>
- Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, 40(S1), S293–S340. <https://doi.org/10.1086/718327>
- Aghion, P., & Howitt, P. (1994). Growth and unemployment. *The Review of Economic Studies*, 61(3), 477–494. <https://doi.org/10.2307/2297900>
- Agrawal, A., Gans, J., & Goldfarb, A. (2018). Prediction machines: The simple economics of artificial intelligence. *Journal of Information Technology Case and Application Research*, 47–53.
- Ancillai, C., Sabatini, A., Gatti, M., & Perna, A. (2023). Digital technology and business model innovation: A systematic literature review and future research agenda. *Technological Forecasting and Social Change*, 188, 122307. <https://doi.org/10.1016/j.techfore.2022.122307>
- Ballestar, M. T., Camiña, E., Díaz-Chao, Á., & Torrent-Sellens, J. (2021). Productivity and employment effects of digital complementarities. *Journal of Innovation & Knowledge*, 6(3), 177–190. <https://doi.org/10.1016/j.jik.2020.10.006>
- Barba Navaretti, G., Castellani, D., & Pieri, F. (2014). Age and firm growth: Evidence from three European countries. *Small Business Economics*, 43(4), 823–837. <https://doi.org/10.1007/s11187-014-9564-6>
- Carbonell, A. F., & Frijters, P. (2004). How important is methodology for the estimates of the determinants of happiness? *The Economic Journal*, 114(497), 641–659. <https://doi.org/10.1111/j.1468-0297.2004.00235.x>
- Chen, Y. M. (2020). Improving market performance in the digital economy. *China Economic Review*, 62, 101482. <https://doi.org/10.1016/j.chieco.2020.101482>
- Chen, J. D., & Wang, J. J. (2021). Industry digitization, local market size and technological innovation. *Modern Economic Research*, 4, 97–107. <https://link.cnki.net/doi/10.13891/j.cnki.mer.2021.04.012>

- Ciarli, T., Kenney, M., Massini, S., & Piscitello, L. (2021). Digital technologies, innovation, and skills: Emerging trajectories and challenges. *Research Policy*, 50(7), 104289. <https://doi.org/10.1016/j.respol.2021.104289>
- Cirillo, V., Evangelista, R., Guarascio, D., & Sostero, M. (2021). Digitalization, routineness and employment: An exploration on Italian task-based data. *Research Policy*, 50(7), 104079. <https://doi.org/10.1016/j.respol.2020.104079>
- Ding, H. Y., & Cheng, Q. W. (2024). Digital innovation, entrepreneurship and green development of manufacturing enterprises. *Science Research Management*, 45(01), 84–97. DOI: 10.19571/j.cnki.1000-2995.2024.01.009.
- Falk, M. (2012). Quantile estimates of the impact of R&D intensity on firm performance. *Small Business Economics*, 39(1), 19–37. <https://doi.org/10.1007/s11187-010-9290-7>
- George, G., Haas, M. R., & Pentland, A. (2014). Big data and management. *Academy of Management Journal*, 57(2), 321–326. <https://doi.org/10.5465/amj.2014.4002>
- Hansen, B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of Econometrics*, 93(2), 345–368. [10.1016/S0304-4076\(99\)00025-1](https://doi.org/10.1016/S0304-4076(99)00025-1)
- Hao, X. L., Wang, X. H., Wu, H. T., & Hao, Y. (2023). Path to sustainable development: Does digital economy matter in manufacturing green total factor productivity? *Sustainable Development*, 31(1), 360–378. <https://doi.org/10.1002/sd.2397>
- Huang, B., Li, H. T., Liu, J. Q., & Lei, J. H. (2023). Digital technology innovation and high-quality development of Chinese Firms - evidence from firms' digital patents. *Economic Research Journal*, 3, 97–115. https://kns.cnki.net/kcms2/article/abstract?v=xEDmK2-VgJk5WWG1tOkn9eqEyUZYNjE8oUa6V_M2uVTNKwctMv-bH4-UcYEqVvUn-vF50cVoFXBzfmSnNZGpxhpWhI9TB9i6o-rtgf8wTsFKe55kq35XBdLLjEbo8HIZIVJ2lbTDyGFC6LaBda-yJJe9iny7R5jkoai99f4J15cFMxKspGHXpZQ-YwRMLCAf2-MTtVIPQ=&uniplatform=NZKPT&language=CHS
- Huang, M., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, 21(2), 155–172. <https://doi.org/10.1177/1094670517752459>
- Iorembor, P. T., Gbaka, S., Işık, A., Nwani, C., & Abbas, J. (2024). New insight into decoupling carbon emissions from economic growth: Do financialization, human capital, and energy security risk matter? *Review of Development Economics*, 28(3), 827–850. <https://doi.org/10.1111/rode.13077>
- Jiang, F. X., Shi, B. B., & Ma, Y. B. (2016). Financial experiences of information publishers and corporate financing constraints. *Economic Research Journal*, 6, 83–97. https://kns.cnki.net/kcms2/article/abstract?v=xEDmK2-VgJgK6GMWf4hBBAQDA5NYNNPie07CPre0W6ID5r8V0IB-SMJLiw3Hg7ngC2s6k3oeusMZgvaOfFu_zk3y31WzrgpvPwglctEDUMc7rgC1qR9qlsWt1rVwzlcG3Bwjc3lAgXXCMCSYSdeGwScHV22HSSBK3aCvSyLIVfaJndP8Z7bN138U_R6bN8VNX7eZatnuFY=&uniplatform=NZKPT&language=CHS
- Khanna, T., & Palepu, K. (2004). Globalization and convergence in corporate governance: Evidence from Infosys and the Indian software industry. *Journal of International Business Studies*, 35(6), 484–507. <https://doi.org/10.1057/palgrave.jibs.8400103>
- Kshetri, N. (2014). The emerging role of Big Data in key development issues: Opportunities, challenges, and concerns. *Big Data & Society*, 1(2), 2053951714564227. <https://doi.org/10.1177/2053951714564227>
- Lever, M. H. C. (1996). Firm size and employment determination in Dutch manufacturing industries. *Small Business Economics*, 8(5), 389–396. <https://doi.org/10.1007/BF00389556>
- Li, P., Abbas, J., Balsalobre-Lorente, D., Wang, Q., Zhang, Q., & Shah, S. A. R. (2024). Impact of sectoral mix on environmental sustainability: How is heterogeneity addressed? *Gondwana Research*, 128, 86–105. <https://doi.org/10.1016/j.gr.2023.09.018>
- Li, Y., Al-Sulaiti, K., Dongling, W., Abbas, J., & Al-Sulaiti, I. (2022). Tax avoidance culture and employees' behavior affect sustainable business performance: The moderating role of corporate social responsibility. *Frontiers in Environmental Science*, 10, 942527. <https://doi.org/10.3389/fenvs.2022.964410>
- Liu, Y., Dong, J., Mei, L., & Shen, R. (2023). Digital innovation and performance of manufacturing firms: An affordance perspective. *Technovation*, 119, 102458. <https://doi.org/10.1016/j.technovation.2022.102458>
- Liu, J. J., Xiong, Z. Q., & Shi, D. Q. (2023). How does the new environmental protection law affect the transformation and upgrading of heavy-polluting enterprises: Based on the dual perspective of internal innovation and external competition. *Soft Sciences*, 11, 28–35. <https://link.cnki.net/doi/10.13956/j.ss.1001-8409.2023.11.05>
- Liu, Y. J., Zhang, X. W., & Shen, Y. (2024). Technology-driven carbon reduction: Analyzing the impact of digital technology on China's carbon emission and its mechanism. *Technological Forecasting and Social Change*, 200, 123124. <https://doi.org/10.1016/j.techfore.2023.123124>
- Li, C., Wang, Y., Zhou, Z., Wang, Z., & Mardani, A. (2023). Digital finance and enterprise financing constraints: Structural characteristics and mechanism identification. *Journal of Business Research*, 165, 114074. <https://doi.org/10.1016/j.jbusres.2023.114074>
- Marston, S., Li, Z., Bandyopadhyay, S., Zhang, J., & Ghalsasi, A. (2011). Cloud computing—the business perspective. *Decision Support Systems*, 51(1), 176–189. <https://doi.org/10.1016/j.dss.2010.12.006>
- Martin, K. (2019). Ethical implications and accountability of algorithms. *Journal of Business Ethics*, 160(4), 835–850. <https://www.jstor.org/stable/45278173> <https://doi.org/10.1007/s10551-018-3921-3>
- Monteiro, G. F. A. (2019). High-growth firms and scale-ups: A review and research agenda. *RAUSP Management Journal*, 54(1), 96–111. <https://doi.org/10.1108/RAUSP-03-2018-0004>
- Moon, H. R., & Weidner, M. (2017). Dynamic linear panel regression models with interactive fixed effects. *Econometric Theory*, 33(1), 158–195. <https://www.jstor.org/stable/26172566> <https://doi.org/10.1017/S0266466615000328>

- Mutascu, M. (2021). Artificial intelligence and unemployment: New insights. *Economic Analysis and Policy*, 69, 653–667. <https://doi.org/10.1016/j.eap.2021.01.012>
- Nambisan, S. (2017). Digital entrepreneurship: Toward a digital technology perspective of entrepreneurship. *Entrepreneurship Theory and Practice*, 41(6), 1029–1055. <https://doi.org/10.1111/etap.12254>
- Nambisan, S., Lyytinen, K. J., Majchrzak, A., & Song, M. (2017). Digital innovation management: Reinventing innovation management research in a digital world. *MIS Quarterly*, 41(1), 223–238. <https://doi.org/10.25300/MISQ/2017/41:1.03>
- Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital business strategy: Toward a next generation of insights. *MIS Quarterly*, 37(2), 471–482. <https://www.jstor.org/stable/43825919> <https://doi.org/10.25300/MISQ/2013/37:2.3>
- Nguyen, Q. P., & Vo, D. H. (2022). Artificial intelligence and unemployment: An international evidence. *Structural Change and Economic Dynamics*, 63, 40–55. <https://doi.org/10.1016/j.strueco.2022.09.003>
- Paeleman, I., Guenster, N., Vanacker, T., & Siqueira, A. C. O. (2023). The consequences of financial leverage: Certified B corporations' advantages compared to common commercial firms. *Journal of Business Ethics*, 189(3), 1–17. <https://doi.org/10.1007/s10551-023-05349-5>
- Peng, H. U. O., & Luxin, W. A. N. G. (2022). Digital economy and business investment efficiency: Inhibiting or facilitating? *Research in International Business and Finance*, 63, 101797. <https://doi.org/10.1016/j.ribaf.2022.101797>
- Porter, M. E., & Heppelmann, J. E. (2014). How smart, connected products are transforming competition. *Harvard Business Review*, 92, 18.
- Postel-Vinay, F. (2002). The dynamics of technological unemployment. *International Economic Review*, 43(3), 737–760. <https://doi.org/10.1111/1468-2354.t01-1-00033>
- Provost, F., & Fawcett, T. (2013). Data science and its relationship to big data and data-driven decision making. *Big Data*, 1(1), 51–59. <https://doi.org/10.1089/big.2013.1508>
- Sakurai, N., Papaconstantinou, G., & Ioannidis, E. (1997). Impact of R&D and technology diffusion on productivity growth: Empirical evidence for 10 OECD countries. *Economic Systems Research*, 9(1), 81–109. <https://doi.org/10.1080/09535319700000006>
- Savrul, M., & Incekara, A. (2015). The effect of R&D intensity on innovation performance: A country level evaluation. *Procedia - Social and Behavioral Sciences*, 210, 388–396. <https://doi.org/10.1016/j.sbspro.2015.11.386>
- Wang, Q. Y. (2015). Fixed-effect panel threshold model using stata. *The Stata Journal: Promoting Communications on Statistics and Stata*, 15(1), 121–134. [10.1177/1536867X1501500108](https://doi.org/10.1177/1536867X1501500108)
- Wang, J., & Chang, H. (2021). Advances in research on the impact of artificial intelligence on the labor market. *Economic Perspectives*, 8, 146–160.
- Wang, S. X., & Luo, J. (2024). A study of the employment skill structure effects of industrial digitization. *Northwest Population*, 2, 114–126. <https://link.cnki.net/doi/10.15884/j.cnki.issn.1007-0672.2024.02.010>
- Xie, F. S., & Kuang, X. L. (2020). Can expanding financial activities of manufacturing firms improve profitability? –taking Chinese A-share listed manufacturing firms as an example. *Management World*, 12, 13–28. <https://link.cnki.net/doi/10.19744/j.cnki.11-1235/f.2020.0180>
- Yang, G. Q., Wang, H. S., Fan, H. S., & Yue, Z. Y. (2023). Carbon emission reduction effects of the digital economy: Theoretical analysis and empirical evidence. *China Industrial Economics*, 5, 80–98. <https://link.cnki.net/doi/10.19581/j.cnki.ciejournal.2023.05.005>
- Yao, X., & Xu, J. (2022). Technological progress, economic cycles and the loss of manufacturing jobs. *The Journal of World Economy*, 5, 81–112. <https://link.cnki.net/doi/10.19985/j.cnki.cassjwe.2022.05.009>
- Yin, S., Yu, Y., & Zhang, N. (2024). The effect of digital green strategic orientation on digital green innovation performance: From the perspective of digital green business model innovation. *Sage Open*, 14(2), 1–23. <https://doi.org/10.1177/21582440241261130>
- Yin, S., & Zhao, Y. (2024a). Digital green value co-creation behavior, digital green network embedding and digital green innovation performance: moderating effects of digital green network fragmentation. *Humanities and Social Sciences Communications*, 11(1), 228. <https://doi.org/10.1057/s41599-024-02691-5>
- Yin, S., & Zhao, Y. (2024b). An agent-based evolutionary system model of the transformation from building material industry (BMI) to green intelligent BMI under supply chain management. *Humanities and Social Sciences Communications*, 11(1), 468. <https://doi.org/10.1057/s41599-024-02988-5>
- Yuan, D. M., Zhou, L., & Yuan, L. (2021). The impact of technological innovation mode shift on the employment structure of labor force - An analysis based on the data of listed manufacturing companies. *Chinese Journal of Population Science*, 06, 81–95. +128. <https://link.cnki.net/urlid/11.1043.C.20211223.1559.014>
- Zhou, Z. H. (2020). Impact of artificial intelligence technology development on employment and response. *Chongqing Social Sciences*, 10, 44–54. <https://link.cnki.net/doi/10.19631/j.cnki.css.2020.010.004>
- Zhu, J. W., Jin, & X., Bei. (2023). The impact of artificial intelligence development on manufacturing employment in China. *Studies in Labor Economics*, 5, 121–143.
- Zhuang, D., Abbas, J., Al-Sulaiti, K., Fahlevi, M., Aljuaid, M., & Saniuk, S. (2022). Land-use and food security in energy transition: Role of food supply. *Frontiers in Sustainable Food Systems*, 6, 1053031. <https://doi.org/10.3389/fsufs.2022.1053031>