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Digital economy’s impact on manufacturing upgrading: evidence from China’s provincial panel data analysis

Ni Zhong
School of Digital Economy and Management, Suzhou City University, Suzhou, China, and

Ming Yu Cheng, Sheik Kyin Tey and Kuk Fai Fok
Faculty of Accounting and Management, Universiti Tunku Abdul Rahman, Kajang, Malaysia

Abstract

Purpose – The purpose of this study is to investigate the impact of digital economy (DE) on China’s manufacturing upgrading (MU), as well as examine the role of human capital (HC) in this process.

Design/methodology/approach – Using a balanced panel data set comprising annual data from 30 provinces in China for the period between 2011 and 2022, this study uses the fixed effects, mediating effects and threshold effect models to assess the impact of DE development on MU in China.

Findings – The research findings indicate that: DE has a significant positive impact on the overall upgrading of the MU in China. DE promotes MU through HC. The relationship between the DE and MU exhibits a non-linear characteristic. Moreover, the influence of the DE on MU presents a trend of nonlinear enhancement. When the development of the DE surpasses a certain threshold, its positive impact on MU becomes significantly more pronounced. In regional heterogeneity analysis, DE significantly promotes MU in medium-low gross domestic product (GDP) regions, but its impact is insignificant in high GDP regions.

Originality/value – This study moves beyond the conventional assumption of a simple linear relationship between the DE and MU, proposing a more complex and realistic model. This study addresses a research gap by investigating the critical yet understudied role of HC as a factor in how the DE drives MU. This study introduces a more economically meaningful method for regional analysis within China by categorising provinces into high-GDP and medium-to-low-GDP groups.

Keywords Digital economy (DE), Manufacturing upgrading (MU), Human capital (HC), Threshold effect

Paper type Research paper

1. Introduction

The rapid advancement of digital technologies has transformed a wide range of industries, with manufacturing being one of the most significantly impacted. As global competition intensifies, the integration of the digital economy (DE) into manufacturing processes has become a strategic priority for many countries. To strengthen competitiveness and drive innovation, nations around the world are actively promoting the digitalisation and intelligent transformation of their manufacturing sectors. This paradigm shift, commonly referred to as Industry 4.0, seeks to leverage digital technologies to optimise production processes, enhance efficiency and create new value propositions (Aceto *et al.*, 2020). Governments around the world have launched national strategies to support this transformation. For example, the US “National Strategy for

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Advanced Manufacturing" (United States Department of Commerce, 2022), Japan's "Society 5.0 Strategy" (Unesco, 2019) and India's "Made in India." The Chinese Government also put significant emphasis on the role of the DE in the manufacturing sector. For example, "Made in China 2025" states that digitalisation, networking and intelligence in manufacturing are the core technologies of the new round of industrial revolution (Wang *et al.*, 2020) and emphasises their critical importance for achieving the ambitious goals of "Made in China 2025."

As the primary beneficiary of China's participation in global value chains, the manufacturing sector has significantly enhanced the nation's international standing and competitiveness, acting as a key driver of economic growth (Wen *et al.*, 2022). However, the sector faces ongoing challenges, including technological bottlenecks in critical core areas, rising labour costs and escalating trade tensions. These factors have made it increasingly difficult for traditional low-tech, low-value-added manufacturing to sustain long-term industry and economic growth (Huang *et al.*, 2021). As a result, promoting manufacturing upgrading (MU) has become a crucial priority in China.

The potential of DE to drive MU has attracted growing attention from both policymakers and academic researchers. While many studies have explored the impact of DE on MU, significant gaps remain in the existing literature that justify further investigation. Although the prevailing view suggests that DE can enhance manufacturing performance, some scholars argue that China's digital economy (DE) remains at a relatively early stage of development, which may limit its capacity to fully drive MU through digital technologies (Guo and Yang, 2021). Most of the existing studies assume a linear relationship between DE and MU. However, given the dynamic nature of technological evolution, changes in industrial structures and shifting policy environments, the impact of DE on MU could be nonlinear, time-varying or influenced by feedback mechanisms. In addition, previous studies have primarily concentrated on the direct effects of the DE on MU, with limited attention given to the underlying mechanisms through which this relationship operates. Although the Chinese Government has placed strong emphasis on the importance of both technological innovation and human capital (HC) in advancing MU (Ministry of Industry and Information Technology of the People's Republic of China, 2025), most empirical research to date has focused predominantly on technological innovation. The role of HC in this process remains relatively underexplored. Because of China's vast geographical size and significant regional disparities in development, the impact of DE on MU is likely to vary across regions. However, existing studies often rely on a broad classification of China into eastern, central and western regions based solely on geographic criteria. This approach does not adequately reflect the varying levels of economic development among provinces.

To address these limitations, this study uses panel data from 30 provinces in China from 2011 to 2022. It aims to examine the relationship between DE and MU and investigate the nonlinear impact of DE on MU in China. Particularly, the role of HC in DE affecting MU is examined. To capture regional heterogeneity more accurately, the 30 provinces are grouped based on economic development levels into high-gross domestic product (GDP) and medium-to-low-GDP categories.

2. Literature review

2.1 The impact of digital economy on manufacturing upgrading

In recent years, an expanding body of literature has investigated the role of DE in enhancing productivity, promoting innovation and supporting the upgrading of manufacturing industries. It is extensively acknowledged that DE plays a pivotal role in promoting MU. Among these contributions, several studies highlight DE's potential to drive sustainable growth in the manufacturing sector (Deng *et al.*, 2022). Specifically, from the perspective of industrial structure, DE plays a crucial role in fostering technological innovation within manufacturing enterprises and in facilitating the sector's structural upgrading (Wang and Wei, 2023; Chen and Zhou, 2024). Besides, DE exerts a positive promotional effect on industrial productivity (Liu *et al.*, 2022). From the global value chain perspective, DE increases the forward participation of manufacturing in global value chains, thereby improving the division of labour in global value chains (Zhou *et al.*, 2022). From the standpoint of green manufacturing development, DE plays a pivotal role in the green transformation of the manufacturing sector (Si *et al.*, 2023). By reducing carbon emissions, digital technology improves industrial performance and fosters green development (Ji *et al.*, 2023). However, some scholars contend that the DE impedes technological progress (Hao *et al.*, 2023). Chinese researchers further elaborate that this negative effect is attributed to the insufficient development of key technologies within China, as well as the adverse effects of digital industrialisation, which includes the drain of talent and capital from other sectors (Guo and Yang, 2021). Besides, the expansion of the DE scale does not significantly contribute to enhancing resource allocation efficiency and fostering product innovation within the manufacturing sector (Li *et al.*, 2024). These divergent views suggest a lack of consensus among scholars concerning DE's capacity to facilitate the development of the manufacturing sector.

Adding further complexity, recent studies suggest that the relationship between DE and manufacturing is far more complex than a simple linear one. As the level of DE development increases, its impact on the manufacturing green development becomes increasingly pronounced (Jia *et al.*, 2023). The existing studies identified an inverted U-shaped trend relationship between DE and manufacturing efficiency. In the initial stages of DE's development, an increase in DE can lead to improved manufacturing efficiency. However, once the DE reaches a certain level of development, its continued expansion may lead to diminishing, and even negative, returns, leading to reduced manufacturing efficiency (Sun *et al.*, 2024). In particular, beyond this development threshold, the DE may create information bottlenecks that raise the marginal cost of information processing for firms within the industrial chain, thereby slightly reducing the overall level of industrial modernisation (Han *et al.*, 2019).

2.2 Mechanisms through which digital economy promotes manufacturing upgrading

Technological innovation is widely recognised as a key mechanism through which DE promotes MU. Numerous studies have confirmed the mediating role of technological innovation in this relationship (Ren *et al.*, 2023). Specifically, DE promotes manufacturing structural upgrading through technological innovation (Chen and Zhou, 2024; Gong *et al.*, 2023; Wu and Shao, 2022). Additionally, Li *et al.* (2024) find that DE significantly increases the total factor productivity of manufacturing enterprises through technological innovation. In addition to technological innovation, several studies have also highlighted the mediating roles of other factors, such as manpower agglomeration (Xie *et al.*, 2025), resource allocation efficiency (Wang *et al.*, 2024) and economies of scale (Li *et al.*, 2024).

2.3 Study on the regional heterogeneity of digital economy affecting manufacturing upgrading

Studies have highlighted significant regional differences in how DE influences MU in China, because of variations in resources, levels of digital development, policy environments and other local conditions (Liu and Hui, 2021; Zhang *et al.*, 2022b). Most studies have observed that DE in eastern China has a significant positive impact on promoting MU, whereas the facilitating effect in western China is not statistically significant (Hao *et al.*, 2023; Xu and

Han, 2022). This disparity may be attributed to the fact that the eastern region generally boasts a higher economic development level and advanced digital infrastructure. In contrast, the western region faces significant challenges in terms of labour structure and technological development, which hinder the ability of manufacturing enterprises to effectively leverage the benefits of the DE (Chang *et al.*, 2023). Furthermore, China's western region is rich in energy resources and plays a crucial role in ensuring the country's energy supply. Consequently, it has a high concentration of industries characterised by high pollution and high energy consumption which is not beneficial for MU (Zhang *et al.*, 2022b). Conversely, some found that the impact of DE on promoting MU in the western region is more significant (Liu *et al.*, 2022). This may be attributed to differences in regional development stages. In the eastern region, where the economy is more advanced and the industrial structure is relatively mature, the effects of DE on MU may have already been largely realised, resulting in slower or more limited additional gains. In contrast, the western region, with its relatively underdeveloped economy and concentration of lower-tier industries, is likely in an earlier phase of digital integration, where the marginal returns from DE are still rising, leading to a more significant impact on MU (Guan *et al.*, 2022).

It is evident that the existing literature has yet to reach a consensus regarding the impact of the DE on MU: some scholars argue that the DE facilitates this process, while others hold the opposite view. This divergence suggests that the relationship between the DE and MU may not be simply linear, but rather exhibit a nonlinear character. However, studies specifically examining such nonlinear dynamics remain limited, and their findings are inconsistent. Further, regarding the mechanisms through which the DE influences MU, most research has focused on the mediating role of technological innovation, while exploration of other potential pathways remains relatively underdeveloped. In particular, although HC is repeatedly emphasised in national policy and empirically validated as a critical driver of manufacturing development (Jibir *et al.*, 2023), its specific mechanisms within the context of DE-driven MU have not been sufficiently examined. Furthermore, when analysing regional heterogeneity in this relationship, most existing studies adopt a conventional geographical division, categorising China into eastern, central and western regions. This classification fails to accurately capture the substantive disparities in economic development levels across regions, potentially obscuring more nuanced regional characteristics.

To address aforementioned research limitations, this study aims to investigate the following three aspects: First, a fixed effects model will be constructed to examine the linear impact of the DE on MU. Second, a mediation effect model will be established to analyse the mechanism of HC in the process of how the DE influences MU. Finally, a panel threshold model will be used to further explore the potential nonlinear relationship between the DE and MU. Theoretically, this research extends the framework of mechanisms through which the DE affects MU, with particular emphasis on the mediating role of HC. Empirically, by introducing a more refined regional classification standard and using a panel threshold model, this study provides new evidence and perspectives for understanding the complexity of the relationship between the two.

3. Theoretical framework and research hypotheses

The relationship between the DE and MU can be understood through the Techno-Economic Paradigm theory, which explains how technological change drives shifts in production models and economic structures. The 21st century has witnessed an accelerated shift in the techno-economic paradigm because of rapid advancements in information technology (Chien *et al.*, 2022). The rise of the DE marks the formation of a new techno-economic paradigm (Gangwar *et al.*, 2022; Knell, 2021). The development of DE is closely associated with the development and widespread application of digital technologies such as big data, artificial intelligence, cloud computing and the Internet of Things. These technologies are at the heart of DE, enabling the digitisation, networking and intelligent transformation of manufacturing processes (Martínez-Caro *et al.*, 2020). DE significantly enhances information sharing capabilities, boosts technological efficiency and facilitates the transition toward intelligent manufacturing for traditional enterprises (Cai *et al.*, 2021), improving total factor productivity in manufacturing (Chang *et al.*, 2023). Therefore, this study proposed the following hypothesis:

H1. Digital economy has a significant positive effect on manufacturing upgrading.

Based on endogenous growth theory, the key endogenous force behind economic growth includes knowledge accumulation, HC and innovation, which all originate from within the system (Clas *et al.*, 2023). The rise of DE has profoundly reshaped industrial organisations and workforce structures (Sima *et al.*, 2020). In a digitalised environment, the demand for highly skilled talent continues to rise. For example, the widespread adoption of digital tools has increased the need for expertise in areas such as data analytics and automation, compelling workers to engage in continuous learning and skill development (Ras *et al.*, 2017). Further, it has shifted enterprise skill requirements and motivated workers to proactively develop their competencies to adapt to this evolving landscape (Grigorescu *et al.*, 2021). By actively adapting to new technologies and evolving job roles, workers develop a crucial capacity for technological adaptability. This capacity is crucial to quickly master future technological shift. Further, equipped with this adaptability and supported by online knowledge networks and digital platforms, workers can significantly accelerate the innovation efficiency. Besides, HC is widely recognised as a critical factor influencing enterprises' performance (Agyabeng-Mensah and Tang, 2021). The HC theory emphasises the value of knowledge, skills and experience acquired through education and training. This theory posits that investing in HC improves labour productivity, benefiting not only individuals but also broader economic development (Robeyns, 2006). Higher levels of education and skill development significantly enhance manufacturing efficiency (Jibir *et al.*, 2023). Skilled labour significantly enhances value-added output in manufacturing (Chandran *et al.*, 2017). Moreover, expanding HC improves the quality of exported manufacturing products (Yue, 2023). Therefore, this study proposed the second hypothesis:

H2. Digital economy influences manufacturing upgrading through human capital.

The effect of DE on MU is complex and may exhibit nonlinear characteristics. In the early stages of DE development, several barriers may limit its effectiveness in promoting MU; these include the lack of well-developed digital infrastructure, bottlenecks in the application and diffusion of digital technologies and constraints in financing and policy support which may hinder its effectiveness. Many firms are reluctant to invest in costly new technologies and may show resistance to digital transformation (Jia *et al.*, 2023). Even among firms that have initiated digitalisation, the lack of skilled technical personnel and the need for an adaptation period may prevent DE from exerting a significant impact on MU in the short term (Chen, 2023). In some cases, it may even act as a hindrance. However, as DE continues to evolve and reach a higher level of development, its positive effects on MU begin to emerge. Improved infrastructure, greater technological readiness and enhanced organisational capacity allow firms to better leverage digital tools for innovation and structural transformation. However, beyond a certain stage of development, DE may begin to reduce manufacturing efficiency, as excessive digitalisation can introduce complexities, coordination costs or information overload that hinder operational performance (Sun *et al.*, 2024). Therefore, this study proposed the third hypothesis:

H3. The effect of the digital economy on manufacturing upgrading is nonlinear, exhibiting threshold characteristics.

Figure 1 displays the theoretical framework of this study.

4. Methodology

4.1 Model

This study uses the fixed effects model to examine the proposed hypotheses. Compared to the random effects model which assumes no correlation between individual effects and explanatory variables that often fail in practice, the fixed effects model provides more reliable estimates (Collischon and Eberl, 2020). In addition, fixed effects model also addresses potential omitted variable and endogeneity issues (Breuer and DeHaan, 2024). Given these advantages, this study uses the fixed effects model to examine the relationship between DE and MU.

To empirically test *H1*, whether DE promotes MU, this study establishes the following model:

$$MU_{it} = \alpha_0 + \alpha_1 DE_{it} + \alpha_2 CV_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where *i* stands for the province and *t* for the year; MU is the MU index; DE denotes the DE development index; CV refers to a set of control variables; μ_i and λ_t represent the province and year fixed effects, respectively; and ε_{it} means the random disturbance term.

To test *H2*, which investigates whether DE influences MU through HC, this study adopts the causal steps approach proposed by Baron and Kenny (1986). Accordingly, the following mediation model is constructed. Equation (2) is used to examine the effect of DE on HC, while equation (3) assesses the joint impact of DE and HC on MU.

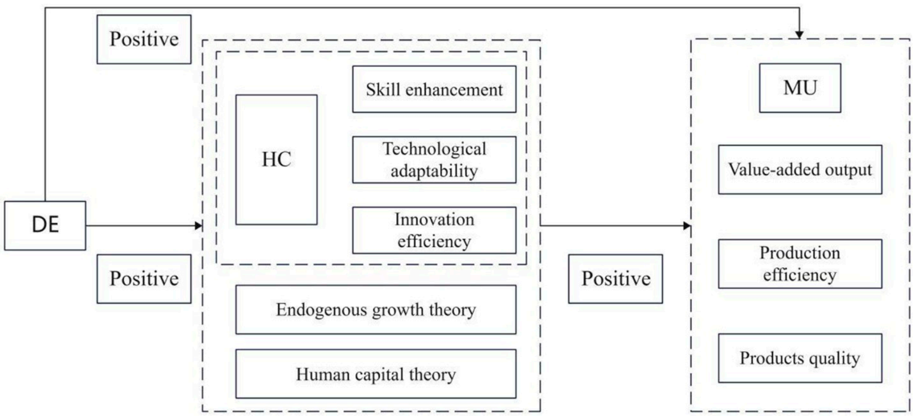

Figure 1. Theoretical framework of the study
Source: Authors' own

$$HC_{it} = \beta_0 + \beta_1 DE_{it} + \beta_2 CV_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

$$MU_{it} = \gamma_0 + \gamma_1 DE_{it} + \gamma_2 HC_{it} + \gamma_3 CV_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

where HC represents human capital.

To investigate *H3*, whether there is nonlinear relationship between the DE and MU, this study uses the panel threshold model proposed by Hansen (1999). This model identifies inflexion points between explanatory variables through a segmentation function (Zheng *et al.*, 2023). It accurately estimates and tests the significance of thresholds without the need for preset theoretical or experiential values. This method endogenously groups sample data, eliminating subjectivity and allowing for significance testing after estimation (Liu *et al.*, 2023a). The following panel threshold model is constructed:

$$MU_{it} = \delta_0 + \delta_1 DE_{it} * I(DE_{it} < \pi) + \delta_2 DE_{it} * I(DE_{it} > \pi) + \delta_3 CV_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

where DE serves as the threshold variable, I represents the indicator function and π denotes the threshold value.

4.2 Variables

4.2.1 Dependent variable: manufacturing upgrading level (MU). Chinese Government proposed many strategies to promote manufacturing development such as "Made in China 2025," which aims at fostering technology innovation and high-end manufacturing. Therefore, this study defines MU as an evolving process from low technology, labour-intensive manufacturing to high technology, innovation-driven manufacturing. Following the study of Zhong and Tao (2022), the percentage of operating income from high-tech manufacturing is selected as an indicator of MU. High-tech manufacturing encompasses advanced production technologies and high value-added products, and an increase in its operating income percentage indicates a shift toward higher technology content and value-added products in the manufacturing sector. According to the classification by the National Bureau of Statistics of China, high-tech manufacturing includes six major categories: pharmaceutical manufacturing, aviation, spacecraft and equipment manufacturing, electronics and communication equipment manufacturing, computer and office equipment manufacturing, medical instrumentation and instrumentation manufacturing and information chemicals manufacturing. The formula for MU is as follows:

$$MU = \frac{high-tech\ manufacturing\ business\ income}{Total\ manufacturing\ business\ income} \quad (5)$$

4.2.2 Independent variable: digital economy development level (DE). DE is a new economic form in which the use of digitised knowledge and information is the key factor of production, modern information networks are the key carrier and the effective use of ICT is an important driving force for efficiency improvement and economic structure optimisation (Zhong *et al.*, 2024). Based on the research of Zhong *et al.* (2024), the study constructs an indicator system comprising four dimensions: digital infrastructure, digital industrialisation, industrial digitisation and digital innovation, to avoid the limitation of using a single indicator to comprehensively assess the development level of the DE. Table 1 presents the indicators of each dimension.

Table 1. Indicator system of digital economy

Dimensions	Indicators	Symbol
Digital infrastructure	Mobile phone penetration rate	+
	Internet penetration rate	+
	Number of internet broadband access ports	+
	Number of domain names	+
	Length of fibre optic cable lines	+
Digital industrialisation	Telecommunications business volume per capita	+
	E-commerce sales	+
	Software business revenue	+
	E-commerce purchases	+
Industrial digitisation	Proportion of enterprises with e-commerce transactions	+
	Number of enterprise-owned websites	+
	Number of websites per 100 companies	+
	Number of computers per 100 people	+
Digital innovation	Proportion of employees in information transmission computer services and software	+
	R&D expenditure/GDP	+
	Number of patent applications	+
	Technology market turnover	+

Source(s): Zhong *et al.* (2024)

Subsequently, the study uses the entropy weighting method to assign values to each indicator objectively and finally derives the DE index of each province from 2011 to 2022 according to the weighting. The higher the index is, the higher the level of DE development. The entropy weighting method is frequently used in empirical studies and used to determine objective weights for multiple variables that are not directly related, thereby calculating a comprehensive index (Zhang *et al.*, 2022a). Compared to principal component analysis, which is also a widely used objective weighting method, many researchers argue that the entropy weighting method generally provides more accurate and interpretable results (Alao *et al.*, 2020; Chen, 2021).

4.2.3 Mediating variable. HC is selected as the mediating variable in this study, based on both theoretical considerations and empirical findings in the existing literature. Most of the research used the following indicators to measure HC: the number of university students (Li and Liu, 2021; Zhao *et al.*, 2022); years of education per capita (Zhang *et al.*, 2021), etc. However, these indicators may not be sufficient to represent the level of HC in the DE (Chen and Zhou, 2024). Building on the work of Chen and Zhou (2024), this study uses the number of research and development (R&D) personnel in industrial enterprises as a proxy for HC.

4.2.4 Control variables. To address the problem of endogeneity resulting from omitted variables, control variables are selected to minimise the influence of other factors on MU and enhance the model fitting. Following the research of Lu and Jiang (2022), this study includes the following control variables:

- *Foreign direct investment (FDI)*: FDI is crucial in promoting MU in China. The capital accumulation and technology spillover effects resulting from FDI can advance the development of the manufacturing industry (Zhao and Yang, 2019). This study adopts the ratio of FDI and GDP to measure FDI.
- *Urbanisation rate (UR)*: As the workforce increasingly shifts from rural to urban areas, population expansion will result in the movement of linked elements and

urban building, influencing the growth of industries (Zhang, 2022b). The study uses the ratio of urban to total population in each region as a metric to gauge the level of urbanisation.

- *Government intervention (GI)*: The development of the industry is closely related to government policies within the framework of China. Government policy support and guidance for the industry are effective means of promoting the upgrading of the manufacturing sector (Guo and Yang, 2021), such as “Made in China 2025.” The study uses the ratio of general budget expenditure to GDP of each Chinese province to measure GI.
- *Wage level (WA)*: The wage level is an important factor that impacts the manufacturing industry. It not only motivates workers by enhancing their job security and competitiveness but also attracts highly skilled labour resources to the industry (Chi *et al.*, 2019). Based on this, the study uses the average wage of manufacturing employees at the provincial to measure the wage level.

4.3 Data resource

The data for this study comprises 30 provinces (autonomous regions, municipalities directly under the central government) of mainland China, from 2011 to 2022, except Tibet. The data were sourced from publications including the China Statistical Yearbook, China Industrial Statistical Yearbook, China High-tech Industry Statistical Yearbook, China Energy Statistical Yearbook, a white paper on China’s DE development, a report on DE Development in Chinese Cities and digital China index report. These sources and publications were selected based on their relevance to the research and their credibility in providing accurate and reliable data.

5. Empirical results and discussion

5.1 Regression results

This study examines the impact of the DE on MU in China, empirically investigating the relationship between the two. A two-way fixed effects model is used to estimate equation (1), aiming to mitigate potential endogeneity issues. Serial correlation and heteroskedasticity are addressed by clustering standard errors at the province level. The regression results, including the stepwise addition of control variables, are presented in Table 2.

In the initial regression without control variables (Column 1), the regression results indicate a significant positive correlation between the DE and MU. Even after incorporating all control variables, as shown in Column 5, this positive correlation remains significant at the 5% level. This finding suggests that the DE fosters MU in China. Specifically, a 1-unit increase in DE development corresponds to a 0.198-units increase in MU.

For the control variables in the study, UR shows a significantly positive effect on MU at the 1% significance level, indicating that higher UR promote MU. Conversely, GI shows a significantly negative coefficient at the 10% level, indicating that increased GI hinders MU. This phenomenon maybe attributed to the distortion of market mechanisms in resource allocation, leading to inefficiencies in production (Liu *et al.*, 2023b). FDI and WA, however, did not yield statistically significant results. FDI presents a dual role for China’s manufacturing sector. Initially, FDI played a pivotal role in integrating China into the global value chain during its early developmental stages, contributing significantly to China’s ascent as the world’s largest manufacturing nation (Fu, 2022). However, FDI’s concentration in low-tech and low value-added sectors may not sufficiently stimulate manufacturing

Table 2. Regression results

Variables	(1)	(2)	(3)	(4)	(5)
DE	0.239** (2.630)	0.236** (2.390)	0.248*** (2.930)	0.227*** (2.820)	0.198** (2.260)
FDI		0.018 (0.130)	−0.151 (−0.890)	−0.054 (−0.330)	−0.180 (−1.490)
UR			0.352 (1.670)	0.289 (1.380)	0.524*** (2.870)
GI				−0.190** (−2.430)	−0.146* (−1.940)
WA					0.008 (1.190)
Constant	0.033* (1.830)	0.033 * (1.830)	−0.152 (−1.370)	−0.070 (−0.600)	−0.229** (−2.090)
Province fixed	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes
Observations	360	360	360	360	360
With in R^2	0.529	0.529	0.568	0.592	0.606

Note(s): The *t*-statistic is in parenthesis. ***, ** and *indicate statistically significant at 1, 5 and 10%, respectively
Source(s): Authors' own

industry upgrading because of constraints in core technology transfer despite capital inflows (Guo and Yang, 2021). Additionally, wage increases might not coincide with improvements in workforce skills. Moreover, in high-tech manufacturing, where research and development costs dominate over labour costs, the impact of wages on MU is negligible.

5.2 Mediating model results

To examine the mediating role of HC in the relationship between DE and MU, this study used the causal steps approach to test the mediating effect. Model 2 is used to test the effect of DE on HC. If this relationship is significant, Model 3 is then applied to examine the combined effect of DE and HC on MU. Table 3 presents the results of Models 2 and 3.

The results of Model 2 indicate that DE has a significant positive impact on HC at the 10% significance level, with a coefficient of 2.484. Next, the combined effect of DE and HC on MU is examined. The results of Model 3 show that both DE and HC have a significant positive impact on MU at the 5% significance level, with coefficients of 0.142 and 0.023, respectively. This finding suggests the presence of a partial mediating effect, thereby supporting *H2*.

Table 3. Results of mediating effect model

Variables	HC Model 2	MU Model 3
DE	2.484* (1.980)	0.142** (2.060)
HC		0.023** (2.560)
FDI	0. 666 (0.440)	−0.195 (−1.520)
UR	5.170*** (2.960)	0.407** (2.210)
GI	−0.980 (−0.550)	−0.124 (−1.420)
WA	−0.007 (−0.140)	0.0.009 (1.180)
Constant	7.453*** (5.950)	−0.397*** (−2.940)
Province fixed	Yes	Yes
Year fixed	Yes	Yes
Observations	360	360
With in R^2	0.480	0.634

Note(s): The *t*-statistic is in parenthesis. ***, ** and *indicate statistically significant at 1, 5 and 10%, respectively
Source(s): Authors' own

5.3 Threshold effects results

To examine the nonlinear relationship between DE and MU, this study uses DE as a threshold variable. Before conducting the threshold test, it is essential to determine the significance of the threshold effect and identify the number of thresholds. Typically, the bootstrap method is used to test whether a variable serves as a threshold and to determine its specific threshold values (Zheng *et al.*, 2023).

In this study, we conducted 300 bootstrap simulations to identify and validate the thresholds. Through 300 iterations of resampling the data, this study examines the presence and significance of the threshold effect. The results are presented in Tables 4 and 5.

Table 4 reveals a double threshold effect of the DE on MU, significant at the 10% levels. Under this double threshold, Table 5 shows that the impact of the DE on MU exhibits a progression from non-significant to weak, then to strong.

Specifically, when the level of DE development is below 0.1106, its impact on MU is not statistically significant. Within the interval of [0.1106, 0.6992], DE significantly promotes MU with the coefficient of 0.111. Moreover, when the DE level exceeds 0.6992, its impact remains significant, with the promotion effect increasing from 0.1106 to 0.1624. This suggests that a higher level of DE development intensifies the promotion effect on MU.

The observed characteristics can be explained by the following factors: In the initial stages of DE, when digital technology and DE were nascent, their impact on MU was limited, primarily confined to consumer services such as shopping and education. However, as digital technology advanced and penetrated the manufacturing sector (Liu and Chen, 2021), its influence on MU became more pronounced. As the DE matures beyond a certain threshold, its effect on promoting MU becomes increasingly evident. Therefore, the first threshold may correspond to the critical point of digital infrastructure penetration, while the second threshold

Table 4. Test of the threshold effect

Threshold variable	Threshold number	F-value	*p*-value	10%	5%	1%	Bootstrap
DE	Single	27.730	0.020**	18.530	21.349	29.823	300
	Double	21.750	0.053*	17.479	22.852	31.177	300

Note(s): ** and *represent significance at the 5 and 10% levels, respectively
Source(s): Authors' own

Table 5. Results of the threshold regression

Variable	*p*-value
DE (DE < 0.1106)	−0.231 (−1.600)
DE (0.1106 ≤ DE ≤ 0.6992)	0.111* (1.790)
DE (DE > 0.6992)	0.162** (2.720)
Constant	−0.062 (−1.350)
Province fixed	Yes
Year fixed	Yes
Observations	360
With in R^2	0.628

Note(s): The *t*-statistic is in parenthesis. ***, ** and * indicate statistically significant at 1, 5 and 10% respectively
Source(s): Authors' own

could be related to the scaled application of data as a factor and the formation of an innovation ecosystem.

5.4 Endogeneity and robustness testing

To ensure the robustness of the regression results, in addition to using clustering robust standard errors to enhance the accuracy of statistical inference in regression analysis, this study uses additional three distinct methods for verification.

5.4.1 System Generalised Method of Moments estimates. The primary sources of endogeneity include omitted variables, measurement errors and bidirectional causality (Eckert and Hohberger, 2023). To mitigate the risks of omitted variables and measurement errors, this study uses a two-way fixed effects model and incorporates a range of control variables. However, considering the potential presence of unobserved variables and the possibility of reverse causality between the DE and MU, this study further adopts the system Generalised Method of Moments (GMM) for robustness testing. GMM model addresses the endogeneity issues (Eckert and Hohberger, 2023), and system GMM, in particular, helps correct for heteroskedasticity and autocorrelation within individuals (Sun and Chen, 2022). In addition, system GMM is considered more suitable for panel data with a small “T” and a large “N” (Khan *et al.*, 2023) and is generally more efficient than difference GMM (Khatib, 2025). Given that this study uses panel data from 30 provinces from 2011 to 2022, the system GMM approach is deemed more appropriate for this study. Table 6 presents the results of system GMM estimates.

To validate the model, this study conducted the Hansen test and Arellano–Bond test. The Hansen test ($p > 0.1$) supports the exogeneity of instrumental variables, confirming their validity. Regarding the Arellano–Bond test, the AR (1) test ($p < 0.1$) confirms first-order serial correlation, a common feature of dynamic panel models. The AR (2) test ($p > 0.1$) indicates no second-order serial correlation, validating the model’s error term specification.

Notably, the results of the system GMM estimation indicate a negative effect of DE on MU at the 10% significance level. This finding contrasts with the positive relationship identified by the fixed effects model. The discrepancy between the two results can largely be attributed to the threshold effect of DE on MU. According to the threshold regression results discussed earlier, the impact of DE on MU is nonlinear, showing a progression from non-

Table 6. Results of system Generalised Method of Moments estimates

Variables	Coefficient	Robust standard error	*t*-statistic	Probability
L1.MU	0.998***	0.125	7.970	0.000
DE	−0.099*	0.055	−1.810	0.070
FDI	0.053	0.173	0.310	0.760
UR	−0.001	0.053	−0.010	0.990
GS	−0.236***	0.068	−3.500	0.000
WA	0.001	0.002	0.440	0.659
Constant	0.082**	0.032	2.580	0.010
Observations		330		
Number of groups		30		
Number of instruments		18		
P-AR (1)		0.002		
P-AR (2)		0.302		
P-Hansen		0.255		

Note(s): ***, ** and *indicate statistically significant at 1, 5 and 10%, respectively
Source(s): Authors’ own

significant, to weak and ultimately to strong as DE level increases. Specifically, only when DE level exceeds the critical threshold of 0.111 does its influence become significantly positive. This suggests that in regions or periods where DE remains below a certain threshold, its development may not promote, and even hinder MU, thus helping to explain the negative coefficient observed in the GMM estimation. This finding further confirms the nonlinear nature of the DE–MU relationship, indicating a transition from an insignificant or even adverse impact to a significantly positive effect as DE develops beyond the threshold level.

5.4.2 Exclusion of central government-controlled municipalities and recalculation of digital economy index. Beijing, Tianjin, Shanghai and Chongqing are China's four municipalities, which possess distinct characteristics in economic, political, demographic and technological development compared to other regions. Following the methodology of Liu *et al.* (2023c), these municipalities are excluded from the sample to mitigate the potential influence of their unique administrative status on the study's outcomes. Subsequently, empirical testing was rerun to ensure the robustness and reliability of the findings. Further, given that various methodologies for calculating the DE index may influence empirical outcomes, this study adopts the principal component analysis method, following the research of Guan *et al.* (2022), to recalculate the index. Subsequently, the original model is re-estimated to assess any resultant changes. The results of these two methods are presented in Table 7.

Column 1 in Table 7 shows the regression results after excluding four municipalities. The coefficient associated with the DE has been observed to change, yet it continues to exert a statistically significant positive effect on MU at the 5% significance level. The empirical finding indicates that the influence of the DE in catalysing the MU is pervasive and transcends the confines of select geographical areas. This observation underscores the universal applicability of the DE's role in fostering manufacturing advancement. Consequently, it offers a compelling basis for guiding governments in the strategic development and effective execution of policies. Column 2 in Table 7 presents the regression results after recalculating DE index. The findings demonstrate that the DE continues to exhibit a statistically significant positive impact on MU. These results align with previous fixed effects model results, affirming the robustness of this study's conclusions.

5.5 Heterogeneity testing

As the world's largest developing country, China exhibits significant regional disparities, not only geographically but also notably in economic development levels. In this study, the 30 provinces are classified into two groups based on their average GDP per capita from 2011 to 2022. The top ten provinces with the highest average GDP per capita (exceeding 60,000 RMB) are categorised as the high-GDP group, which includes Beijing, Shanghai, Jiangsu, Tianjin, Zhejiang, Fujian, Guangdong, Inner Mongolia, Shandong and Hubei. The remaining 20 provinces are classified as the medium-low GDP group. The threshold of 60,000 RMB for average GDP per capita was selected based on the empirical distribution of provincial GDP per capita during the study period (2011–2022). This value serves as a natural cut-off point that effectively separates the top ten provinces with the highest levels of economic development. These provinces consistently demonstrate stronger economic performance, more advanced infrastructure and higher levels of DE development compared to the rest. This classification offers a more accurate representation of each region's level of economic development. Building upon this classification, the study further investigates the heterogeneous impact of the DE on MU. This approach aims to generate more targeted

Table 7. Regression results after excluding four municipalities and recalculating digital economy index

Variable	(1)	(2)
DE	0.203** (2.170)	0.014*** (4.080)
FDI	−0.158 (−1.220)	−0.139 (−1.190)
UR	0.380* (1.740)	0.574*** (3.540)
GI	−0.137* (−1.810)	−0.207** (−3.040)
WA	−0.003 (−0.370)	0.006 (0.930)
Constant	0.033* (1.830)	−0.185* (−1.850)
Province fixed	Yes	Yes
Year fixed	Yes	Yes
Observations	360	360
With in R^2	0.633	0.630

Note(s): The *t*-statistic is in parenthesis. ***, ** and *indicate statistically significant at 1, 5 and 10% respectively
Source(s): Authors' own

policy recommendations and development strategies that are aligned with the specific economic conditions of each region. The regression results are presented in Table 8.

As indicated in Table 8, the coefficient representing the impact of DE development on MU is significant at the 5% level for the medium-low GDP groups, with a value of 0.344. However, for the high-GDP group, there is insufficient evidence to support a significant impact.

This phenomenon can be attributed to several factors: First, provinces in the high-GDP group (such as Beijing, Shanghai and Jiangsu) exhibit advanced economic development and relatively mature industrial systems. While these provinces have achieved a high level of DE development, their manufacturing sectors have largely undergone initial rounds of transformation and have already entered a stage of high-quality development. The agglomeration of production factors, technological pathways and infrastructure systems in these regions tend to be stable and

Table 8. Regression results for medium-low gross domestic product and high gross domestic product groups

Variable	(1) Medium-low GDP group	(2) High GDP group
DE	0.344*** (3.860)	0.158 (1.070)
FDI	−0.203* (−1.770)	−0.377 (−1.770)
UR	0.396* (2.000)	1.047** (2.630)
GI	−0.196*** (−3.440)	−0.059 (−0.240)
WA	−0.009 (−1.010)	0.022** (2.600)
Constant	−0.079 (−0.800)	−0.684** (-2.320)
Province fixed	Yes	Yes
Year fixed	Yes	Yes
Observations	240	120
With in R^2	0.699	0.590

Note(s): The *t*-statistic is in parenthesis. ***, ** and *indicate statistically significant at 1, 5 and 10% respectively
Source(s): Authors' own

well-established. As a result, the marginal effect of further DE development on MU is limited. By contrast, medium-low GDP regions, though lagging in both economic and DE development, are often in the midst of rapid structural transformation. These regions typically face underdeveloped infrastructure, lower levels of industrial sophistication and a narrow industrial base (Hu and Wang, 2022). In such contexts, the expansion of DE can significantly enhance foundational infrastructure, improve resource allocation efficiency and boost productivity. Because of their lower starting points, DE generates more substantial and visible improvements in these areas. In addition, regional differences in labour factor endowments also influence the extent to which DE contributes to MU. High-GDP provinces are typically characterised by higher levels of HC, elevated labour costs and a dense concentration of technical talent. In such regions, manufacturing enterprises often possess strong digital literacy, and many firms have already undergone substantial digital transformation. As a result, the marginal benefits of further digital development may be limited. In contrast, medium-low GDP provinces face lower levels of HC and often experience shortages of skilled technical labour. However, these challenges also create opportunities. The advancement of the DE in these regions has facilitated significant improvements in the structure and productivity of the manufacturing sector. Digital reforms, along with efforts to cultivate digital skills and talent, have enhanced labour productivity and technological capacity in manufacturing enterprises. Consequently, the DE tends to play a more prominent and transformative role in driving MU in medium-low GDP regions. Further, medium-low GDP regions often receive heightened policy support and greater allocation of resources aimed at advancing their local economies. Government initiatives promoting the DE tend to prioritise these regions, fostering accelerated digital transformation within their manufacturing industries (Miu and Yang, 2021).

6. Conclusions

6.1 Conclusion and policy recommendations

Based on panel data from 30 provinces in China spanning 2011–2022, this study uses both fixed effects and threshold effect models to analyse the impact of the DE on MU. Further, casual steps approach is used to examine the mediating role of HC. In addition, this study divides 30 provinces in to medium-low GDP and high-GDP groups to examine the heterogeneity effect.

The findings yield several conclusions: overall, DE significantly promotes manufacturing industry upgrading in China. Double threshold effects are observed in the impact of the DE on MU. Specifically, at lower levels of DE development, there is no significant effect on MU. As the DE progresses and reaches the first threshold, it significantly enhances MU. Further increases beyond the second threshold amplify this promotion effect. HC is a main mediator between the relationship of DE and MU. Regional disparities exist in the impact of DE on MU in China. DE has been shown to significantly contribute to MU in medium-low regions.

In summary, based on these conclusions, this study proposes the following recommendations: In light of the double threshold effect of the DE on MU, policies should be dynamically adjusted according to the development level of the DE in different regions. For regions where DE development remains below the first threshold (0.1106), policy efforts should focus on bridging the digital divide to help these areas surpass this critical threshold. Strategic emphasis should be placed on enhancing DE development across multiple fronts. Key areas include digital infrastructure, digital industrialisation, industrial digitisation and digital innovation. For regions where the development of the DE falls between the two thresholds (0.1106–0.6992), the policy focus should transition to promoting the application of digital technologies within enterprises. In regions that have surpassed the second threshold (0.6992), policy efforts should be directed toward fostering a more sophisticated innovation ecosystem, supporting businesses in integrating and applying key frontier technologies throughout R&D and production processes. The mediating role of HC is strengthened. To fully leverage HC as a core bridge in DE-driven MU, policies must precisely target three pathways: upgrading skill structures, enhancing innovation efficiency and optimising technology adaptability. Example include reforming the vocational education system, establishing specialised digital skills training funds or implementing tax incentives and incentive policies for manufacturing R&D personnel. Recognising disparities in regional development levels of the DE underscores the importance of tailored strategies. Regions with lower and medium GDP levels demonstrate significant benefits from the DE in enhancing manufacturing upgrades. Accordingly, policies should be carefully crafted to align with local conditions, thereby enabling these regions to effectively leverage DE potentials for stimulating local economic development.

6.2 Limitation and future research

This study adopts the proportion of operating income from high-tech manufacturing to present the level of MU. While this indicator captures the key goal of China's current industrial transformation, shifting toward high-tech and innovation-driven manufacturing, it may not fully capture the complexity of MU. Especially as the industrial landscape continues to evolve and national policy priorities shift, the connotation and appropriate measurement of MU may also change. Therefore, future research could explore broader dimensions of MU in China and develop more comprehensive indicators.

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Corresponding author
Ni Zhong can be contacted at: zhongni2022@163.com