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Dynamic Nonlinear Relationship between Digital Transformation, Green Transformation in Manufacturing Industry and Labor Structure: Evidence from Panel VAR Analysis

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ABSTRACT

The digital transformation of manufacturing industry can promote the development of green transformation and promote the differentiation of workers' skill structure; On the other hand, it will also hinder the green development due to the huge energy consumption generated by the application of digital technology and facilities. In addition, the green transformation of manufacturing industry will also have differentiated impacts on the employment of labour with different skills due to the innovation of green technology. The existing research has not discussed too much about the interaction among the digital transformation and green transformation in manufacturing industry and labour structure. So, this paper uses the PVAR model to examine the dynamic relationship between digital and green transformation within the industrial sector from the perspective of labour structure, specifically analyzing the impact difference across regions. The results suggest that there is a reciprocal connection between the digitization of manufacturing sector and the labour structure, particularly in the eastern region of China, but the overall interaction between the two remains weak. The interactive between the green transformation of manufacturing industry and the labour structure in the central and western areas has been delayed over periods 1-6. Digital and green manufacturing transformation reinforce each other in central and western regions. However, the digital revolution in the manufacturing industry is hindered by the green transformation in eastern region.

KEYWORDS

Digital transformation of manufacturing industry; Green transformation of manufacturing industry; Labor structure; Dynamic interactive

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1. Introduction

The 20th National Congress of the Communist Party of China has put out the proposition to promote the advancement of high-end, intelligent, and environmentally sustainable development within the manufacturing industry. Additionally, it aims to assist the profound integration of the digital economy with the tangible economy. The higher productivity qualities of digital technology have the potential to bring about a revolution in traditional industrial practices. The optimization of production efficiency has the potential to enable the transition towards sustainable manufacturing practices, hence fostering the promotion of green transformation within the sector (Sharma et al., 2022). Nevertheless, it is important to note that the digital technology sector is naturally characterized by a significant need for energy, leading to the classification of data centers as “energy monsters”. This phenomenon further contributes to the exacerbation of the “green paradox” commonly associated with digital technology. Therefore, it is crucial to advocate for the digitization of the manufacturing sector with the commitment to sustainability in order to mitigate the potential occurrence of the “green paradox” resulting from digital technology (Bakry et al., 2023). According to Gallego and Kurer (2022), the progression of digital technology is expected to result in the partial displacement of the workforce. However, it is vital to note that the digitization of the manufacturing sector is intricately linked to the trained labour. The adoption of digital technology holds promise in its ability to supplement the high-skilled workforce and address the productivity paradox commonly connected with its implementation (Usabiaga et al., 2022).

Prior research mostly concentrated on examining the unidirectional influence of digital transformation in manufacturing on green transformation (Sarkis et al.,2021; Sharma et al., 2022). Additionally, it explored the distinct effects of manufacturing digital transformation or green development on the employment of various skilled labour groups (Chakraborty et al., 2023; Cavenaile,2021). However, few studies have focused on the long-term dynamic interaction between digital transformation and green transformation of manufacturing industry and labor structure. The objective of this study is to explore the interactive impact of digital transformation and green transformation in manufacturing industry from the perspective of labour structure. First, this research needs to address the challenge of accurately and reasonably assessing the digital transformation and green transformation index within the manufacturing industry. Currently, there is a lack of a standardized approach for quantifying the two types of transformation index. After conducting a thorough review of current literature on the measurement techniques employed in assessing the digital transformation and green transformation of the manufacturing industry, we have determined that it is appropriate to construct comprehensive evaluation index system. Subsequently, we will employ the entropy weight approach to produce the aforementioned index. The data source primarily consists of publicly available data from numerous statistical yearbooks. Specifically, we have incorporated the index of industrial robot installation density into the existing index system for measuring the progress of digital transformation in the manufacturing industry. This addition allows us to better gauge the extent to which digital technologies are being utilized in this sector. A high installation density of industrial robots serves as an indicator of advanced digital technology adoption within the manufacturing industry. The data used for this index is sourced from the International Federation of Robotics. Furthermore, as indicated by numerous extant studies, the composition of labour force is typically assessed based on the quantity of individuals employed at varying levels of educational attainment. Specifically, the labor force with college degree or above is regarded as high-skilled force, while those lacking a college degree are classified as medium-low skilled labour. The labour structure can be represented by utilizing the ratio between the number of high-skilled workforce and the number of medium-low skilled workforce. As the ratio increases, there is a constant optimization of the labour structure. In addition, to facilitate a comparative analysis of the disparities between the national sample and the regional sample, and to conduct a more comprehensive investigation into the interplay between the digital transformation of the manufacturing sector, the labour structure, and the green transformation of the manufacturing industry, we partitioned the country into three distinct regions: eastern, central and western. The selected time frame for the samples is from 2007 to 2020. The decision to exclude a longer period of data prior to 2007 is mostly based on the shift in statistical quality and the significant amount of missing data. Furthermore, it is worth noting that the period from 2011 to 2020 can be considered a significant era in China's new economic development, particularly with the emergence of the mobile Internet. However, it is important to acknowledge that a time span of only 10 years may not be ideal for constructing a panel vector autoregressive model. Consequently, this study has opted to utilize data from the period spanning 2007 to 2020 in order to examine the long-term fluctuations in the dynamic interaction connection.

In comparison to the existing literature, the present study posits several potential innovation points. Firstly, this study represents an early exploration of the interplay between digital transformation and green transformation within the manufacturing industry, with a specific focus on labour structure. Notably, this investigation takes place within the context of China, a fast developing nation. By addressing the research gap in related research fields, this paper finds that due to the different transformation stages, the digital transformation and green transformation of manufacturing sector in central and western regions are mutually empowering, while the green transformation of manufacturing industry in the eastern region is an obstacle to digital transformation. It shows that the transformation level in the eastern region is relatively fast and high, but it has entered the stage of energy rebound effect brought by digitization, which is worthy of attention. Secondly, in order to avoid the endogenous problem, this paper adopts panel vector autoregressive model (PVAR) to study the long-term interaction between the digital transformation of manufacturing industry, the labour structure, and the green transformation of manufacturing sector. This analysis controls for various factors such as the level of foreign direct investment, the level of financial development, per capita education expenditure, urbanization level, and industrial structure. By incorporating these controls, the study aims to enhance the credibility and reliability of the research findings. Finally, this study analyzes the influence of labour structure on the synergistic interaction between the digital transformation and the green transformation in manufacturing sector. By answering the above questions, we can better promote the coordination between the digital transformation and the green transformation of manufacturing industry, realize the organic combination of digital economy and real economy, promote the high-quality development of manufacturing industry, and provide a practical basis for the government to formulate policies according to local conditions and accelerate the promotion of the new industrialization.

The paper's chapter structure is outlined as follows: Part 2 mainly introduces the literature review on the relationship between the digital transformation of manufacturing industry, the labour structure, and the green transformation of manufacturing industry. Part 3 mainly introduces the index system and analysis of measurement results of digital transformation and green transformation in manufacturing sector. Part 4 mainly introduces the model construction and the data source of each variable in the model, and also introduces the descriptive statistical results of the three variables that this study focuses on. Part 5 mainly introduces the use of PVAR model for empirical test and result analysis, including GMM regression, unit circle test, Granger causality test, impulse response and variance decomposition. Part 6 provides the main research conclusions and measures of this study.

2. Literature Review

2.1. Digital transformation of manufacturing industry and labor structure

With the accelerated pace of technological advancement, the adoption of "machine substitution" has emerged as a crucial strategy for enterprises to enhance their competitiveness. Consequently, the employment landscape is undergoing a significant transformation. Hutter and Weber (2021) highlight that digitization and intelligence enhance labor productivity, but also accelerate the differentiation of labor skills. The substitution effect of technology on labor will further drive the adjustment and optimization of labor structure. Simultaneously, the skill-biased nature of technological progress has a noteworthy impact on the optimization of industrial, quality, and spatial structures of labor. This promotes a rise in the relative marginal output of high-skilled labor, leading to a continued increase in the proportion of high-skilled labor force employment (Fossen and Sorgner, 2022; Laddha et al., 2022). Cavenaile (2021) discovered a "polarization" phenomenon in the employment structure of the manufacturing workforce, where the income of high- and low-skilled labor increased while the income of middle-skilled labor decreased, due to the impact of high-tech equipment and R&D investment. Harrigan et al. (2021) have highlighted that companies offering middle-income wages exhibit slower growth and fewer job opportunities compared to those offering high and low incomes, ultimately resulting in labor market polarization. The research conducted by Liu and Zhang (2022) revealed that the elevated cost of living and the relocation of labor-intensive manufacturing from developed regions have a detrimental impact on the low-skilled labor force, while having a negligible effect on the highly skilled labor force. In China, the implementation of industrial intelligence in the eastern coastal regions is expected to result in a decline in the demand for labor with a high school education or lower, while in the southern coastal regions, the implementation of industrial intelligence is expected to lead to a decrease in the demand for labor with a junior high school education or lower (Sun and Hou, 2019). Michaels et al. (2014) demonstrated that the rising level of digitization has heightened the need for both highly educated labor and low-skilled labor. Furthermore, the implementation of information and communication technology (ICT) and industrial robotics can optimize the labor structure by augmenting the knowledge and productivity of the workforce (Jongwanich et al., 2022). Other studies have demonstrated a positive correlation between the digitization of enterprises and the presence of a highly skilled workforce (Usabiaga et al., 2022).

2.2. Green transformation of manufacturing industry and labor structure

Green transformation entails a comprehensive overhaul of the system, encompassing the adaptation of business models, innovation in technological processes, and a shift in production modes, which will inevitably affect the employment structure of the labor force (Magacho et al., 2023). Ferris et al. (2014) have highlighted that the green transformation of the manufacturing industry, driven by environmental regulations, may result in significant job losses in high-energy-consuming and high-pollution sectors, particularly among low-skilled workers. Raff and Earnhart (2022) discovered that environmental regulations have a favorable effect on employment structure by facilitating the gradual substitution of low-skilled labor with high-skilled labor that is environmentally conscious. Domguia et al. (2022) posit that environmental regulations will incentivize or compel manufacturing enterprises to engage in technological innovation and adopt cleaner production methods, thereby creating additional green employment opportunities and achieving a mutually beneficial outcome for both industrial sustainability and labor employment. Environmental regulations, whether formal or informal, have an optimizing effect on the structure of labor skills (Chakraborty et al., 2023). Liao et al. (2023) empirically demonstrate that the introduction of the new environmental protection law has exacerbated the adverse effects of environmental regulation on the employment of heavy polluting enterprises. This is due to the imposition of stricter environmental penalties, financing constraints resulting from poor environmental performance, and the difficulty of achieving short-term economic benefits, all of which have led to a reduction in job opportunities.

2.3. Digital transformation and green transformation in manufacturing industry

The crux of the digital revolution in the manufacturing sector lies in the adoption of digital technologies, which boast advanced features and facilitate enhanced production efficiency (Sharma et al., 2022). Isensee et al. (2020) suggest that digital empowerment has the potential to facilitate the green transformation of enterprises by transforming their management and business models. Fallahpour et al. (2021) discovered that digital empowerment facilitates the green transformation of manufacturing enterprises by leveraging technological progress and scale effects. The former stems from the technological advancements generated by digital empowerment, while the latter arises from the expansion of the enterprise's own scale or the industrial agglomeration in the region where the enterprise is situated. Furthermore, digital empowerment drives the green transformation of upstream and downstream manufacturing enterprises in the industrial chain through spillover effects. Ding et al. (2023) found that digitization can optimize the business environment, drive enterprises' innovation behavior, and improve innovation efficiency. In addition, the role of digital technology is realized by creating value through data elements, specifically through the generation, agglomeration, analysis and application of carbon trading data and industry-related data, to promote the construction of carbon trading market and industrial collaborative agglomeration. Carbon trading can promote green development by promoting technological progress, factor accumulation, energy conversion and so on (Liu et al., 2023). Industrial agglomeration can enhance industrial complementarity, promote the progress of green technology, and promote the green development of regional industries (Ding et al., 2022b). Mondejar et al. (2021) discovered that while digitization can facilitate industrial greening through the intelligent acquisition and analysis of green data, it can also exacerbate regional disparities by exerting varying effects on different areas. Lange et al. (2020) note that while digital technology can enhance energy efficiency and reduce energy intensity, its development and utilization may also result in a certain degree of energy consumption escalation. For instance, the Internet enhances the convenience of human production and daily life, effectively mitigating per capita energy consumption via network information consumption. However, the operation and utilization of associated infrastructure and equipment will markedly augment per capita energy consumption. Furthermore, the rapid expansion of the Internet is concomitant with a substantial surge in electricity consumption (Santarius et al., 2023). Sarkis et al. (2021) propose an "inverted U-shaped" relationship between digitization and greening, where the inhibitory effect of digitization improves energy efficiency and reduces energy consumption, however, the dependence of digitization on energy consumption may lead to the "energy rebound effect", exacerbating energy consumption pressures. Hence, there is a need for further exploration of the interplay between digital and green transformation in the manufacturing industry.

Based on the above analysis, the existing literature discusses the relationship between the digital transformation of manufacturing, the green transformation of manufacturing and labor structure, which provides a basis for the research of this paper. Existing studies have primarily focused on analyzing the unidirectional impact of digital transformation in manufacturing on green transformation, while neglecting the potential endogenous and lagged effects among variables. It is impossible to explore the dynamic interaction between variables. This paper constructs a PVAR model based on panel data from 30 provinces, municipalities, and autonomous regions in China (excluding Tibet, Hong Kong, Macao, and Taiwan) from 2007 to 2020. The model analyzes the dynamic interaction relationship between digital transformation and green transformation of the manufacturing industry and its regional heterogeneity from the perspective of labor structure.

3. Measurement and analysis of digital transformation and green transformation in manufacturing industry

3.1. Construction and Measurement of Index System

This paper presents a comprehensive index system for measuring the digital transformation of the manufacturing industry across four dimensions: transformation benefits, foundational elements, innovation levels, and new technology applications (Acemoglu and Restrepo, 2020; Gu et al., 2023). The index system for green transformation in the manufacturing industry is primarily constructed based on three key aspects: growth benefits, innovation drivers, and energy conservation and emission reduction (Sheng and Liu, 2023). Specific indicators are shown in table 1. All indicators were standardized using range normalization to obtain dimensionless data. The entropy weight method was employed to compute the digital transformation index (DTM) and the green transformation index (GTM) of manufacturing industry.

Table 1. Comprehensive evaluation index system of China's manufacturing industry digital and green transformation.

Target layer	Level 1 indicator layer	Level 2 indicator layer	Attribute
Digital transformation of manufacturing industry	Transformation benefit	Total profits of the manufacturing industry per unit of regional GDP	+
		Total fixed assets of the manufacturing industry per unit of regional GDP	+
	Transformation foundation	Mobile phone switch capacity	+
		Length of long-distance fiber cable routes	+
		Sum of Internet and telephone users as a proportion of national users	+
	Innovation level	Number of invention patent applications of industrial enterprises per R&D personnel	+
		Proportion of sales revenue of industrial new products in industrial main business revenue	+
	Digital technology applications	Proportion of software product revenue in industrial main business revenue	+
		Industrial robot installation density	+
		Proportion of main business revenue of the electronic information manufacturing industry in the main business revenue of the industrial sector	+
Green transformation of manufacturing industry	Growth benefits	Proportion of main operating revenue of high-tech manufacturing industry in the main operating revenue of industrial sector	+
	Innovation drive	Proportion of industrial R&D expenses in industrial main business income	+
		Proportion of employees number in high-tech industries in total number of people employed in manufacturing sector	+
	Energy saving and emission reduction	Chemical oxygen demand emissions per unit of industrial added value	-
		Sulphur dioxide emissions per unit of industrial added value	-
		Solid waste generation per unit of industrial added value	-
		Energy consumption per unit of industrial added value	-
		Industrial soot emissions per unit of industrial added value	-
		Water consumption per unit of industrial added value	-
		Industrial governance input per unit of industrial added value	+

In Table 1, the formula for calculating the installation density of industrial robots is as follows. First, divide the number of employment in manufacturing sub-industries in each province of China by the total number of employees in the country. Then the installation density of industrial robots in each province is the product of the installed amount of industrial robots in different industries and the above ratio. The installation volume of industrial robots by industry is primarily determined by the data on industrial robot installations in China, as reported by the International Federation of Robotics (IFR) (Acemoglu and Restrepo, 2020). As industry data is only available from 2007 to 2019, the report by Zhiyan Consulting serves as a valuable supplement for the year 2020.

3.2. Analysis of indicator measurement results

Figure 1 depicts the temporal evolution of China's indices for digital and green transformation in manufacturing industry. As depicted in Figure 1, between 2007 and 2020, the indices for digital and green transformation in manufacturing exhibited an upward trajectory. However, their magnitudes remained relatively low, underscoring the potential for significant advancements in both domains.

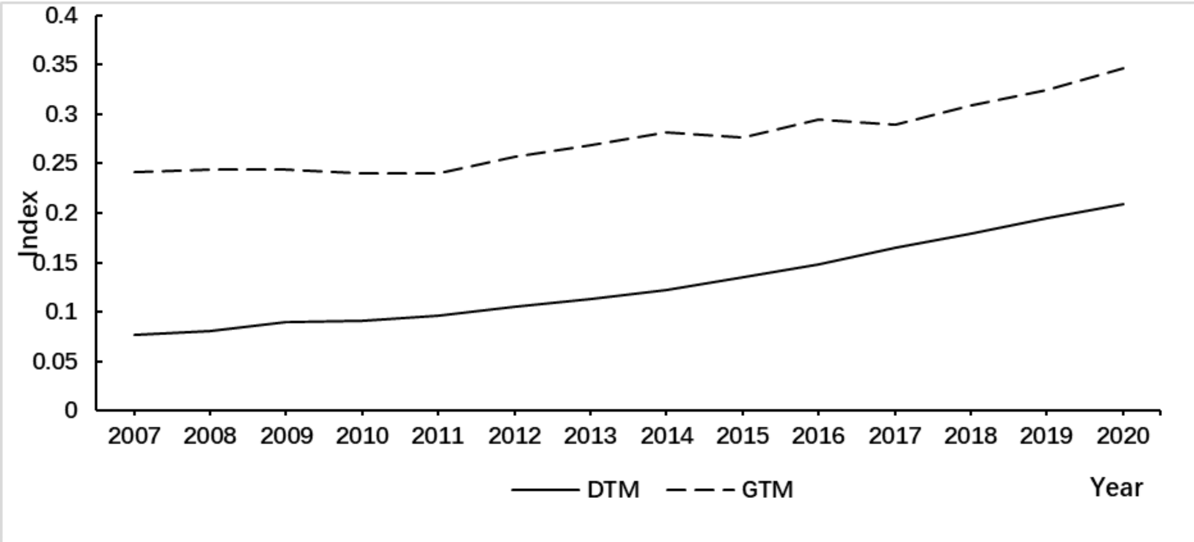

Figure 1. Temporal trend chart of digital transformation index and green transformation index of the manufacturing industry.

4. Model building and data description

4.1. Panel Vector Autoregressive Model (PVAR)

The panel vector autoregressive model (PVAR) integrates both endogenous and exogenous variables within a single endogenous system, thereby capturing the dynamic interplay among all variables. Compared to static single equations, the PVAR model is a simultaneous equation model that effectively mitigates the endogenous influence of parameter estimation results. It also controls for individual fixed effects and time fixed effects that are not easily observable, and predicts the nonlinear effects of external shocks using the orthogonalized impulse response function method. This paper presents an analysis framework that encompasses the digital and green transformation of the manufacturing industry, as well as the labor structure. To achieve this, we have developed a PVAR model (Tzeremes et al., 2023; Chen et al., 2022).

$$y_{it} = \alpha_0 + \sum_{j=1}^{n} A_j y_{i,t-j} + f_i + d_t + u_{it} \tag{1}$$

$$y_{it} = \begin{Bmatrix} dtm \\ gtm \\ ls \end{Bmatrix} \tag{2}$$

In the formula, y_{it} represents the core variables, namely the Digital transformation index (DTM), Green transformation index (GTM), and Labor structure (LS); i, t, and j represent the province, year, and lagging period, respectively; α_0 indicates intercept; A_j represents the parameter matrix; f_i stands for individual fixation effect and reflects the individual heterogeneity of samples on the cross-section; d_t stands for time effect, which reflects the temporal trend of variables; u_{it} stands for random perturbation term and follows a normal distribution.

The labour structure (LS) is measured by the ratio of the number of employed high-skilled labor force to the number of employed low- and medium-skilled labor, in which those employed with college degree or above are regarded as high-skilled labor; employed persons with less than a college degree are considered low-and medium-skilled laborers. The higher the LS value, the more optimized the labor structure.

4.2. control variables

This paper selected “foreign direct investment level, financial development level, per capita education expenditure, urbanization level, industrial structure” as control variables. Among them, foreign direct investment is expressed by the ratio of foreign direct investment to GDP of each province, and the level of opening up can accelerate the import of complex and advanced digital and green technologies from aboard, thus contributing to the transformation and upgrading of China’s industrial structure (Mao et al.,2019). The level of financial development is calculated by the proportion of deposits and loans in GDP of each province. Sufficient financial support can effectively provide funds for the digital transformation and green transformation of the manufacturing industry (Knuth,2018). Per capita expenditure on education is calculated by the ratio of fiscal expenditure on education to the population of each province. The higher the per capita education expenditure level, the higher the education level of the labour force, which can have a positive impact on the transformation and upgrading of the manufacturing industry and enhancement of regional innovation level (Tong et al., 2020). The urbanization level is calculated by the ratio of the urban population to total population in each province. The high urbanization level can gather more production factors for the digital and green development of manufacturing industry (Han and Cao, 2022). The industrial structure is expressed by the ratio of the added value of the tertiary industry to the local GDP of each province, and the upgrading of the industrial structure of each province can provide support for the digitization and green development of the manufacturing industry (Hao et al., 2023).

4.3. Data sources

From 2007 to 2020, the balance panel data of 30 provinces, autonomous regions and municipalities in China (excluding Tibet, Hong Kong, Macao and Taiwan) were selected for empirical analysis, and the original data of each variable were derived from the China Industrial Statistical Yearbook, China Statistical Yearbook, China Science and Technology Statistical Yearbook, China Tertiary Industry Statistical Yearbook, China Energy Statistical Yearbook, China Environment Statistical Yearbook, China Labor Statistics Yearbook, China Electronic Information Industry Statistical Yearbook, China High-tech Industry Statistical Yearbook, the report of the International Robot Alliance Network and the statistical yearbooks of various provinces, individual missing data are completed by differential integration of moving average autoregressive models and other methods.

4.4. Descriptive statistics

Table 2 is a descriptive statistical table of main variables, and statistical analysis is carried out from the national level and the three regions of Eastern, Central and Western. The results show that the level of digital transformation index, green transformation index and labor structure in each region is different, showing regional heterogeneity.

Table 2. Descriptive statistics of main variables.

Region	Variables	Obs	Min	Max	Mean	Std.dev
National	DTM	420	0.017	0.604	0.131	0.083
	GTM	420	0.103	0.623	0.271	0.099
	LS	420	0.031	1.703	0.224	0.220
Eastern	DTM	154	0.017	0.604	0.179	0.101
	GTM	154	0.141	0.575	0.330	0.106
	LS	154	0.046	1.703	0.337	0.320
Central	DTM	126	0.042	0.267	0.112	0.047
	GTM	126	0.146	0.520	0.238	0.061
	LS	126	0.035	0.341	0.158	0.072
Western	DTM	140	0.022	0.313	0.094	0.056
	GTM	140	0.103	0.623	0.237	0.086
	LS	140	0.031	0.410	0.160	0.085

Notes: In this table, the eastern region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the central region includes Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei and Hunan; the western region includes Guangxi, Guizhou, Yunnan,Shaanxi, Chongqing, Sichuan, Qinghai, Xinjiang, Gansu and Ningxia.

5. Empirical testing and result analysis

5.1. Unit root test and cointegration test

To ensure the stationarity of all variables, this study uses the homogeneity LLC test and heterogeneous IPS test, thereby mitigating the potential pseudoregression problem caused by nonstationary panel data. The results in Table 3 indicate that certain series in DTM, GTM, and LS cannot pass the unit root test. However, all series pass the test after undergoing first-order difference operation, suggesting that the three variables are both stable under the state of first-order difference. The Kao test method in the cointegration test is further used to examine the aforementioned variables. The results show that the t value of ADF in the national sample is 7.616, and the corresponding p value is 0.000. The t value of ADF in the eastern sample is 4.055, and the corresponding p value is 0.000. The t value of ADF in the central sample is 1.462, and the corresponding p value is 0.072. Lastly, the t value of ADF in western sample is 3.965 and the corresponding p value is 0.000. The aforementioned results demonstrate that all variables in the national, eastern, central, and western samples reject the null hypothesis at a significance level of at least 10%, suggesting in the long run, there is a cointegration relationship among the three variables in all samples, and the PVAR model can be established.

Table 3. Unit root test.

Region	Test	Variable						Conclusion
		DTM	D.DTM	GTM	D.GTM	LS	D.LS	
National	LLC	-0.578	-16.935***	-4.797***	-13.679***	-8.678***	-16.266***	Stationary
	IPS	2.879	-10.907***	-1.488*	-9.866***	-2.252**	-9.845***	
Eastern	LLC	0.180	-10.250***	-3.179***	-8.096***	-4.555***	-12.175***	
	IPS	5.787	-4.863***	-1.583*	-5.438***	-1.389*	-4.570***	
Central	LLC	-0.062	-4.461***	-1.703**	-5.398***	-5.946***	-5.960***	
	IPS	-0.402	-2.629***	0.853	-2.874***	-1.634*	-5.372***	
Western	LLC	-1.103	-7.437***	-3.957***	-8.597***	-4.588***	-6.264***	
	IPS	1.822	-4.708***	-0.700	-7.827***	-1.549*	-5.823***	

*Notes: ***, ** and * are significant levels of 1%, 5% and 10%, respectively; D. Indicates that the variable has undergone first-order difference operation; The values in the table correspond to the adjusted t-statistic of the LLC test and the Wt-bar statistic of the IPS test.*

5.2. Selection of optimal lag order

The maximum lag order is set to 3, and the minimum values of MAIC, MBIC, and MQIC statistics are comprehensively compared. It can be seen from Table 4 that the optimal lag order of the PVAR model in the whole country and the eastern, central and western regions is both set as order 1.

Table 4. Determination of optimal lag order.

Region	Lag order	MAIC	MBIC	MQIC
National	1	-8.327	-108.329*	-48.348*
	2	-20.260*	-86.928	-46.941
	3	-14.944	-48.278	-28.285
Eastern	1	-25.145*	-98.058*	-54.719*
	2	-20.753	-69.362	-40.469
	3	-16.26	-40.564	-26.118
Central	1	-24.570*	-92.065*	-51.788*
	2	-24.163	-69.16	-42.309
	3	-9.508	-32.006	-18.58
Western	1	-21.460*	-91.800*	-49.928*
	2	-12.253	-59.147	-31.232
	3	-4.676	-28.123	-14.165

*Notes: * indicates the optimal lag order selected under the corresponding criterion.*

5.3. GMM estimation of the PVAR model

Table 5 presents the GMM estimation results, where the digital transformation index is the dependent variable for group 1. The results indicate a significant positive impact of the one-period-lagged digital transformation of manufacturing industry on its own development, highlighting the dependence of the current digital transformation level on the past digital development. The one-period-lagged green transformation of manufacturing industry has a significant negative impact on the digital transformation of manufacturing industry in the eastern region, while it has a positive impact in the central and western regions. The one-period-lagged labour structure exerts a substantial positive influence on the digital transformation of manufacturing sector.

Table 5. GMM estimation results of the PVAR model.

Group1 DTM	National	Eastern	Central	Western
DTM_{it-1}	1.030***（0.000）	1.026***（0.000）	0.520***（0.000）	0.888***（0.000）
GTM_{it-1}	-0.079*（0.094）	-0.254***（0.000）	0.281***（0.000）	0.010*（0.056）
LS_{it-1}	0.051***（0.008）	0.024**（0.017）	0.120***（0.000）	0.060***（0.000）
Time fixed effects	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Hansen's J	77.013（0.110）	48.200（0.345）	88.105（0.276）	99.188（0.238）
Group 2 GTM	National	Eastern	Central	Western
DTM_{it-1}	0.865***（0.000）	0.438***（0.000）	0.258**（0.038）	2.134***（0.000）
GTM_{it-1}	0.343*（0.071）	0.215**（0.017）	1.048***（0.000）	-0.311***（0.000）
LS_{it-1}	-0.139*（0.052）	0.027*（0.074）	0.286***（0.000）	-0.266***（0.000）
Time fixed effects	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Hansen's J	77.013（0.110）	48.200（0.345）	88.105（0.276）	99.188（0.238）
Group 3 LS	National	Eastern	Central	Western
DTM_{it-1}	0.677**（0.046）	0.707***（0.002）	1.374***（0.000）	0.218***（0.000）
GTM_{it-1}	-0.883***（0.001）	-0.949***（0.000）	-0.776***（0.000）	0.148***（0.000）
LS_{it-1}	0.754***（0.000）	0.535***（0.000）	0.487***（0.000）	0.526***（0.000）
Time fixed effects	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Hansen's J	77.013（0.110）	48.200（0.345）	88.105（0.276）	99.188（0.238）

*Notes: ***, **, * are significant levels of 1%, 5% and 10%, respectively; the values in parentheses are P values; it-1 represents the variable first-order lag.*

Table 5, Group 2 reveals that the one-period-lagged digital transformation in manufacturing industry has a noteworthy positive influence on green transformation. This suggests that digital transformation empowers production efficiency, thereby facilitating green transformation. In the eastern and central regions, the one-period-lagged green transformation of manufacturing industry has a significant positive impact on itself, and the one-period-lagged labour structure has a significant positive impact on the green transformation of manufacturing industry. However, in the western region, the above effects are all manifested as significant negative effects.

In Group 3 of Table 5, taking labour structure as the dependent variable, the results show that the one-period-lagged digital transformation of manufacturing industry of all samples has a significant positive impact on the labour structure. The impact of the one-period-lagged green transformation of manufacturing industry on labour structure is significantly negative in the eastern and central regions, and significantly positive in the western region. The impact of the one-period-lagged labour structure on itself is significant and positive.

5.4. Granger causality test

The unit circle test is performed before the Granger causality test, and when the reciprocal modulus of the eigenvalue modulus accompanying the matrix in the PVAR model is in the unit circle, it means that the constructed PVAR model meets the stability conditions. Figure 2 shows that in the national, eastern, central and western samples, the reciprocal of each eigenvalue modulus is located in the unit circle, that is, the PVAR model constructed in this paper meets the stability conditions.

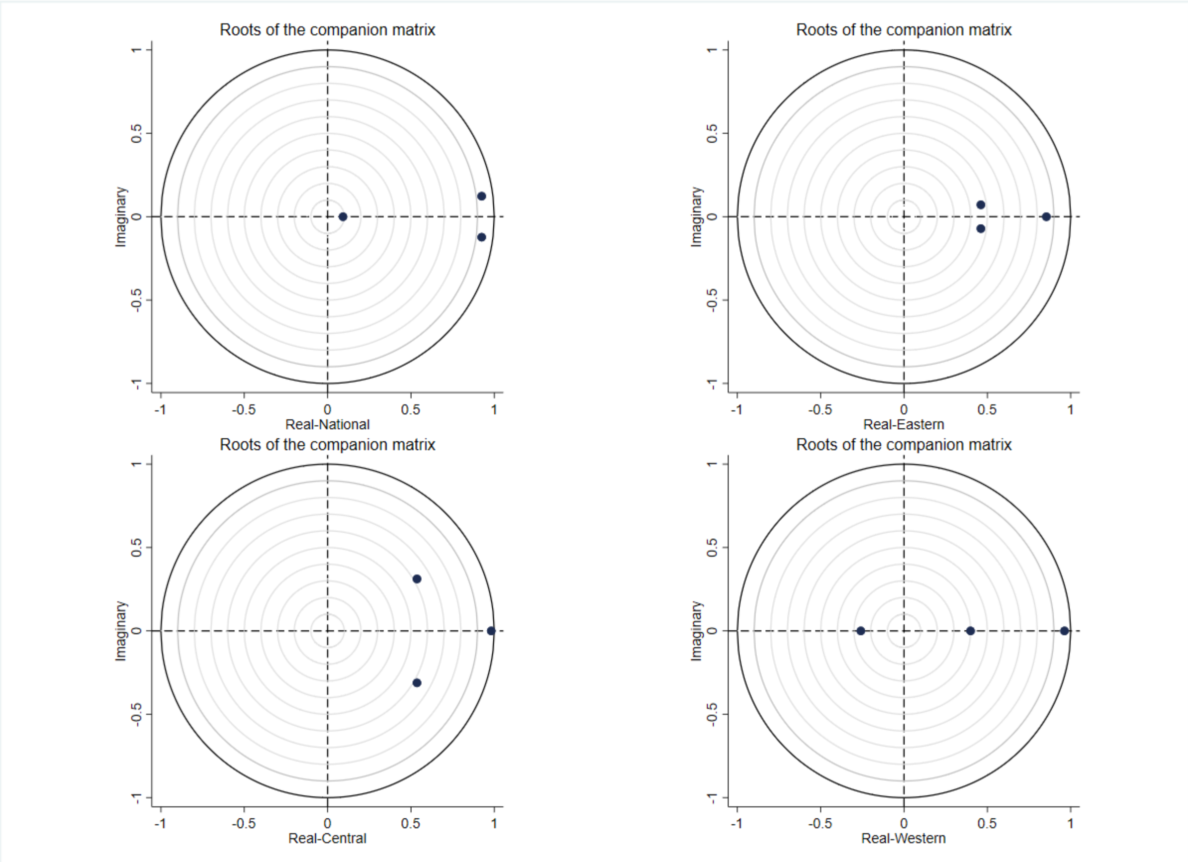

Figure 2. Stability test of the PVAR model.

In order to further verify whether there is a causal relationship among the variables, the Granger causality test with a lag of 1 order is adopted for each variable. The results in Table 6 show that there is a two-way Granger causal relationship among the digital transformation of manufacturing industry, the green transformation of manufacturing industry and labour structure, which is consistent with GMM regression estimation.

Table 6. Granger causality test.

Null hypothesis	Chi-square statistical value			
	National	Eastern	Central	Western
DTM is not a granger reason for GTM	27.825***	17.399***	4.303**	580.376***
	(0.000)	(0.000)	(0.038)	(0.000)
DTM is not a granger reason for LS	3.986**	9.272***	135.422***	14.744***
	(0.046)	(0.002)	(0.000)	(0.000)
GTM is not a granger reason for DTM	2.810*	36.088***	368.077***	3.660*
	(0.094)	(0.000)	(0.000)	(0.056)
GTM is not a granger reason for LS	11.125***	27.799***	105.927***	89.110***
	(0.001)	(0.000)	(0.000)	(0.000)
LS is not a granger reason for DTM	6.976***	5.742**	49.102***	48.333***
	(0.008)	(0.017)	(0.000)	(0.000)
LS is not a granger reason for GTM	17.767***	3.195*	41.592***	57.777***
	(0.000)	(0.074)	(0.000)	(0.000)

*Notes: In parentheses are the significance level P values, ***, **, * 1%, 5%, 10% significance levels, respectively.*

5.5. Impulse response analysis

The impulse response of the PVAR model analyzes the dynamic interaction between two variables when other variables are unchanged, so as to characterize the long-term equilibrium relationship between each variable. In this paper, the orthogonalized impulse response function (IRF) is used to analyze the interaction relationship between variables in the next 10 periods to measure the current and future changes of the response variables with time after being externally shocked by the unit standard deviation of the shock variable.

5.5.1. Impulse response analysis in national samples

In Figure 3, (a), (e) and (i) show that the impacts of the digital transformation of manufacturing industry, the green transformation of manufacturing industry and the labour structure in the first two periods are significantly positive on themselves, indicating that all three have certain economic inertia in the short term, which is manifested as a good self-reinforcing effect.

(c) and (g) in Figure 3 show that the labour structure and the digital transformation of manufacturing industry in the first three periods show a good mutual promotion effect, indicating that the high-skilled labour force plays an important role in promoting the digital transformation of manufacturing industry. Starting from the fourth period, the digital transformation of manufacturing industry has a negative impact on the labour structure, and gradually tends to zero, that is, the digital transformation of manufacturing industry promotes and hinders the labor structure in the short and long term, respectively.

(b) and (d) in Figure 3 show that the labour structure and the green transformation of manufacturing industry in the first two periods hinder each other, but from the third period, the labor structure has a positive impact on the green transformation of manufacturing industry, indicating that the high-skilled labor force promotes the green transformation of manufacturing industry, but there is a certain lag.

(f) and (h) in Figure 3 show that the digital transformation of manufacturing industry promotes the green transformation, but the green transformation has a restraining effect on the digital transformation.

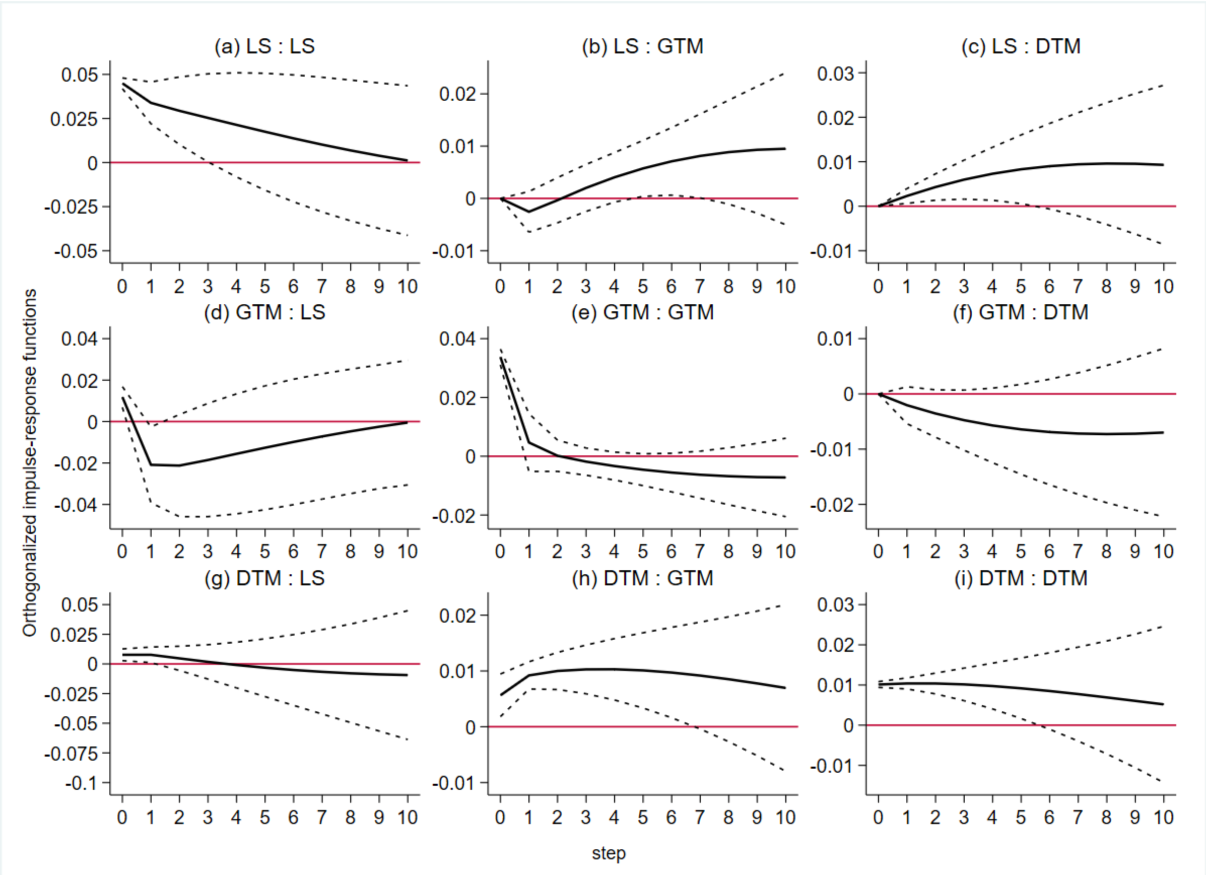

Figure 3. Impulse response function at the national level.

5.5.2. Impulse response analysis in the eastern, central and western regions

Samples from the eastern, central and western regions were used for impulse response analysis and comparative analysis, as shown in Figures 4, 5 and 6.

(1) The interaction between the digital transformation of manufacturing industry and the labour structure is more pronounced in the eastern region. From Figures 4 to 6 (c) and (g), it can be seen that the digital transformation of manufacturing industry and labour structure in the eastern, central and western regions all show mutual promotion, indicating that high-skilled labour has a promoting effect on the digital transformation of the manufacturing industry, and the digital transformation of manufacturing industry also promotes the optimization of labour structure and increases the proportion of high-skilled labor employment. The comparative analysis shows that the interaction between the digital transformation of manufacturing industry and the labour structure in the eastern region is more significant. (c) and (g) in Figure 4 show that in the eastern region, the positive impact of labour structure on the digital transformation of manufacturing industry reached a maximum of 0.002 in Period 2, and then gradually weakened and approached 0. The positive impact of digital transformation of manufacturing industry on labour structure gradually weakened from a maximum value of 0.02 and gradually approached 0 over time. The reasons for the analysis are that the high level of digitization of the manufacturing industry in the eastern region can provide more intelligent emerging jobs, thereby increasing the proportion of high-skilled labour(Santos et al., 2023). As an important element of human capital, the highly skilled workforce further promotes the digital transformation of manufacturing industry, resulting in mutually reinforcing positive interactions.

(2) The interaction between the green transformation of manufacturing industry and the labour structure is more significant and responsive in the central region. Compared with (b) in Figures 4 to 6, the impact of labour

structure on the green transformation of manufacturing in the western region turned from negative to positive in the second period, which was first suppressed and then promoted, and the eastern and central regions have always shown a significant positive impact, indicating that high-skilled labour can promote the green transformation of manufacturing in the long run. Among them, the promotion effect in the central region is more significant, reaching a maximum of 0.0125 in the Second period. Comparing (d) in Figures 4 to 6, it is found that the green transformation of manufacturing industry in the western region has a positive impact on the labour structure, but its effect is small, reaching a maximum of 0.005 in the first period; In the first five periods, the green transformation of manufacturing industry in the eastern and central regions showed a negative impact on the labour structure, but the central region responded more quickly, reaching a minimum of -0.02 in the first period, and a promoting effect in the sixth period, and then gradually approaching 0. The reasons for the analysis are that the green transformation of manufacturing industry in the eastern region is accompanied by industrial structure adjustment, and the proportion of tertiary industry continues to increase, which increases the employment number of low-skilled labor to a certain extent, and is manifested in the impulse response function that the green transformation of manufacturing has a negative impact on the labor structure. While undertaking the industrial transfer of eastern region, the central and western regions pay attention to the green transformation, which provides more jobs for the high-skilled labour force, and the green transformation of manufacturing industry has a significant positive impact on the labour structure in the impulse response function.

(3) The interaction between the digital transformation and the green transformation of manufacturing industry is more significant in the western region. Comparing (f) in Figures 4 to 6, it is found that the green transformation of manufacturing in the eastern region has a restraining effect on digital transformation, but it is a promotion effect in the central and western regions. The reasons for the analysis are that in the early stage of the green transformation of manufacturing industry, enterprises accelerated green innovation through the use of digital technology, which in turn promoted the digital transformation to a certain extent, and the green transformation in the central and western regions is in this period. With the gradual deepening of the digital transformation and green transformation of manufacturing industry, the problem of high energy consumption caused by digitization has attracted attention, and the green transformation will inhibit the digital transformation based on traditional high-carbon energy, and the green transformation of manufacturing industry in the eastern region is in this period. However, by increasing green energy and making energy low-carbon, the inhibition effect of green transformation of manufacturing industry on digital transformation will gradually weaken, so the digital transformation of manufacturing industry needs to be promoted in tandem with low-carbon energy development (Bakry et al., 2023). Comparing (h) in Figures 4 to 6, it is found that the digital transformation of manufacturing industry in the eastern, central and western regions has promoted the green transformation, which is consistent with existing research. The digital transformation of manufacturing industry in the western region responded faster and more significantly to the promotion of green transformation, reaching a maximum of 0.015 in the first period, and then gradually weakening and approaching 0. This shows that the digital transformation and green transformation of manufacturing industry in the western region are relatively slow, but the mutual promotion between the two is more significant, so as to better promote the high-quality development of the manufacturing industry.

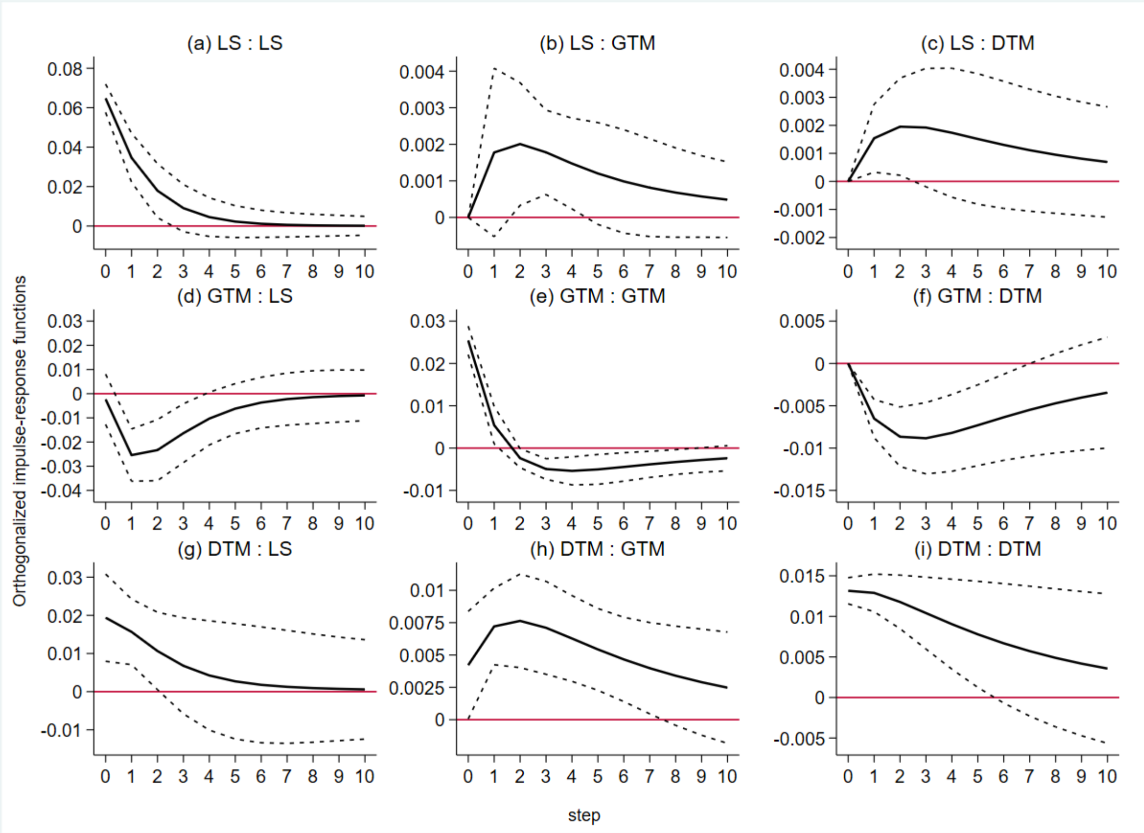

Figure 4. Impulse response function at the eastern level.

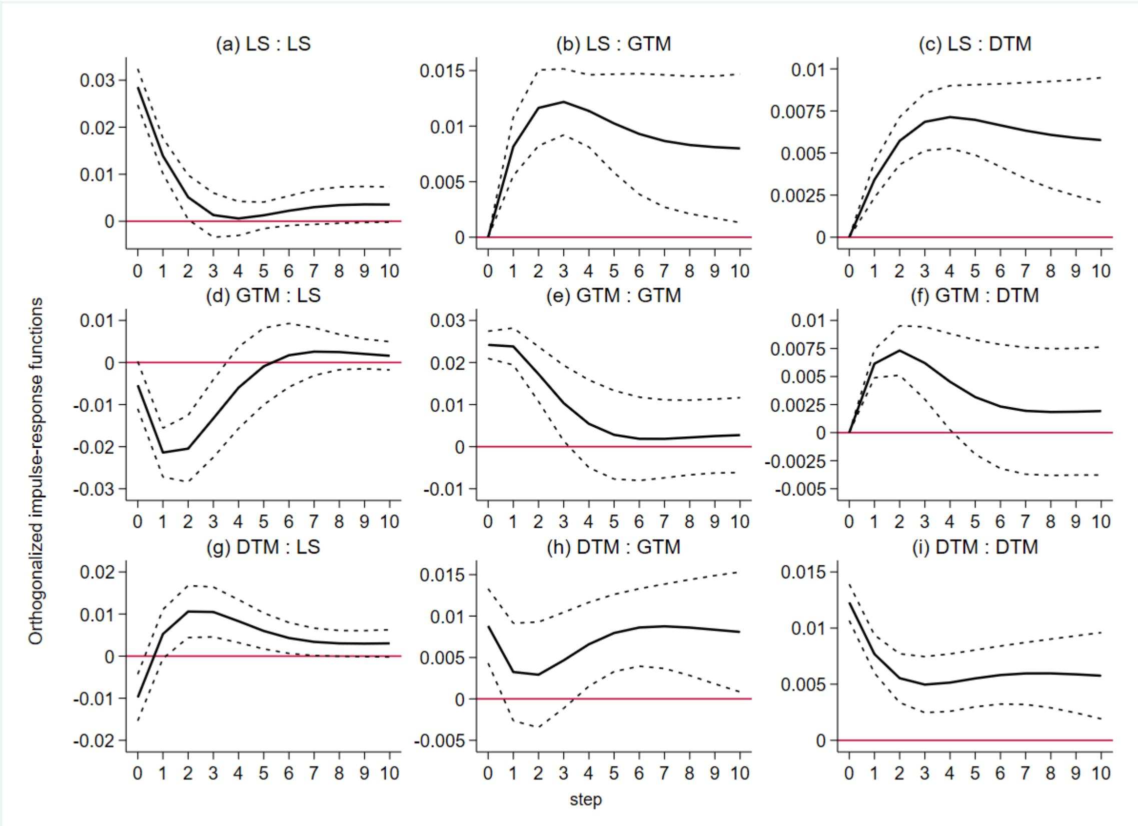

Figure 5. Impulse response function at the central level.

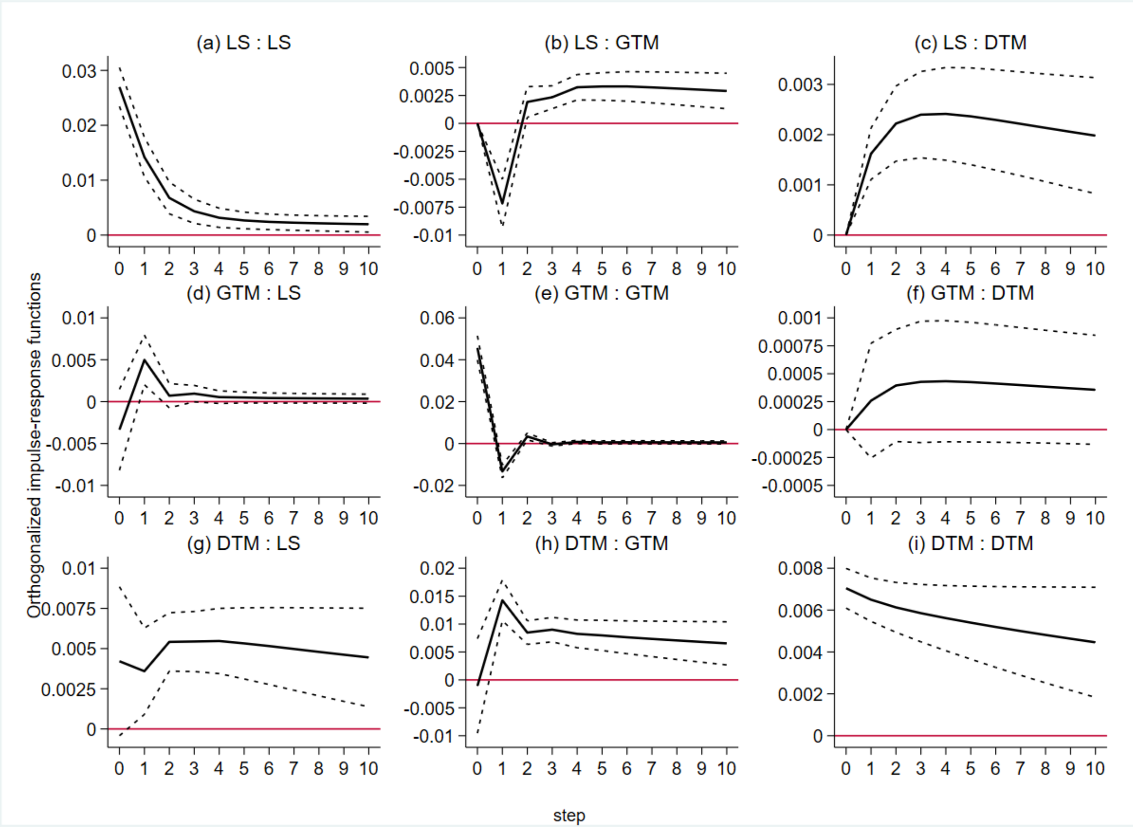

Figure 6. Impulse response function at the western level.

5.6. Variance decomposition results

The long-term interaction between the digital transformation of manufacturing industry, green transformation of manufacturing industry and labor structure is further measured by variance decomposition, and the degree of interaction between different variables has been analyzed. As can be seen from Table 7, the variance decomposition results for period 10 and 20 did not change much, indicating that the contribution rate of each shock to variable changes after period 10 remained stable. Through variance decomposition, it can be found that:

From the national level, the contribution rate of digital transformation of manufacturing industry, green transformation of manufacturing industry and labour structure to their own variance is high, all above 40%, but the variance contribution rate of the interaction between the two is low, all below 40%, indicating that the interaction among the three is weak.

From the perspective of different regions, the contribution rate of labor structure in the eastern region to the digital transformation and green transformation of manufacturing industry is only about 1.5%, indicating that the proportion of high-skilled labor employment in the eastern region needs to continue to increase, so as to better promote the digital transformation and green transformation of manufacturing industry. The variance contribution rate of the green transformation of manufacturing industry to digital transformation in the central region is less than 18%, and the variance contribution rate of manufacturing digitization to greening and labour structure is less than 30%, indicating that the central region needs to further improve the ability of green technology and digital innovation, and enhance the dynamic interaction among the green transformation and the digital transformation of manufacturing industry and the labour structure. In the western region, the contribution rate of digital transformation of manufacturing industry to its own variance is more than 86%, and the contribution rate of labor structure to its own variance is also more than 70%, indicating that although the digital transformation of manufacturing industry in the western region is slower and the proportion of high-skilled labor employment is low, it has a self-reinforcing effect.

Table 7. Variance decomposition.

Variables	Period	DTM				GTM				LS			
		(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
DTM	10	0.489	0.656	0.469	0.877	0.330	0.268	0.173	0.225	0.045	0.098	0.184	0.185
	20	0.362	0.646	0.466	0.862	0.273	0.277	0.254	0.290	0.117	0.098	0.202	0.261
GTM	10	0.190	0.329	0.179	0.004	0.536	0.717	0.535	0.736	0.241	0.197	0.419	0.029
	20	0.233	0.338	0.134	0.004	0.467	0.709	0.402	0.657	0.232	0.197	0.395	0.027
LS	10	0.320	0.015	0.352	0.119	0.134	0.014	0.292	0.039	0.714	0.705	0.397	0.785
	20	0.405	0.015	0.400	0.134	0.261	0.015	0.344	0.053	0.652	0.705	0.403	0.713

Notes: The values in the table are the results of 200 simulations using the Monte Carlo method;(1), (2), (3) and (4) represent the whole country, the eastern region, the central region, and the western region.

In the above empirical process, this paper considers the above-mentioned control variables, including “level of foreign direct investment, level of financial development, per capita education expenditure, level of urbanization and industrial structure”, and the empirical results have not changed much, and the conclusion is relatively stable.

6. Research conclusions and suggestions

6.1. Conclusions

Compared to static analysis, this paper employs a PVAR model to dynamically examine the interplay between digital and green transformations in the manufacturing industry, with a focus on labour structure, using provincial panel data from 2007 to 2020. Regional heterogeneity is also analyzed. The following conclusions can be drawn: (1) The digital transformation of manufacturing industry and the labour structure mutually reinforce each other, yet the interaction between the two remains weak. This suggests that the current labor structure falls short of meeting the demands of the digital transformation of manufacturing industry. (2) The labour structure exerts a positive influence on the green transformation of manufacturing industry, with regional heterogeneity observed in the impact of the latter on the former. Specifically, the long-term effect is positive in the central and western regions, but negative in the eastern region. (3) The digitization of the manufacturing sector has the potential to facilitate the transition towards a more sustainable practices. However, the impact of this green transformation on the digitization of manufacturing industry exhibits regional heterogeneity, with positive effects observed in the central and western regions, and negative impacts in the eastern regions.

6.2. Suggestions

Building on the aforementioned findings, this paper proposes the following recommendations to advance the harmonious integration of digital and green transformations in the manufacturing sector:

Firstly, optimize the labor structure and expedite the digital transformation of the manufacturing sector in a continuous manner. To enhance the contribution of highly skilled labor in driving digital transformation within the manufacturing industry, optimization of labor structure is imperative at three levels: manufacturing enterprises, workers, and governments. At the level of manufacturing enterprises, during the process of digital transformation, we aim to enhance the skills of enterprise workers by introducing highly skilled talents and providing on-the-job training. At the labor level, workers ought to enhance their comprehensive competencies in accordance with the demands of their roles, facilitate the refinement of labor composition, and proficiently leverage the impact of highly skilled labor on digital productivity. At the governmental level, in light of the positive externality of human capital development, it is imperative to augment investments in education and emerging technology workforce training. This will not only boost the labor employment rate but also ensure a steady supply of high-skilled labor for the digital transformation of the manufacturing industry.

Secondly, in conjunction with the present state of regional industrial development, tailor policies to local circumstances to facilitate the eco-friendly metamorphosis of the manufacturing sector. As a crucial aspect of industrial transfer from the eastern region, the central and western regions must enhance their investment in human capital, optimize their labor structure, and increase the proportion of high-skilled labor employment. Additionally, they should encourage green technology innovation in enterprises, prioritize the protection of the ecological environment while pursuing rapid growth, and promote the high-quality development of the manufacturing industry. For the rapidly developing eastern region, it is imperative to accelerate the growth of productive service industries, particularly those that are complementary to manufacturing. This will facilitate the orderly agglomeration of productive service industries, which can better serve the green transformation of manufacturing (Du and Zhang, 2023). And this approach can increase the employment of highly skilled labor through the correlation and interaction between the green transformation of manufacturing and the agglomeration of high-end productive service industries. In addition, the government should moderately increase innovation subsidies for small and medium-sized manufacturing enterprises, reduce their innovation costs (Ding et al., 2022a), encourage them to actively carry out green innovation activities, cultivate green innovation capabilities, and then promote the green development of manufacturing industry.

Thirdly, fully leverage the potential of highly skilled labor to enhance the synergy between digital and green transformations in the manufacturing industry. Due to the significant reliance of digital technology on conventional high-carbon energy sources, the “green paradox” of digital technology gradually surfaces as the digital and green transformations of the manufacturing industry reach a certain level. To address the "green paradox", we must simultaneously advance the digitization of manufacturing and the development of low-carbon energy. This requires promoting the growth of new energy industries and aligning clean energy supply with digital technology development. Additionally, the manufacturing industry’s digital and green transformations should be viewed as key targets and drivers of economic development. To achieve this, it is necessary to further increase the R&D investment of colleges and universities, promote the improvement of the conversion rate of scientific research achievements, and drive the industrial growth(Zhu et al., 2022); At the same time, we should leverage the high-level technology absorption and learning abilities of skilled labor, fostering a complementary relationship between high-skilled labor, digital technology, and green technology. This will improve production and energy efficiency, promoting coordinated development of the manufacturing industry’s digital and green transformation.

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Conflict of interest

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

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