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Digitization inputs and global value chain of manufacturing industry in China

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Article

Keywords: digitization inputs, manufacturing industry, global value chain, China

Posted Date: May 5th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9264330/v1

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Additional Declarations: No competing interests reported.

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Abstract

The rapid advancement of digital economy has necessitated digital transformation in the global manufacturing industry. Information and communication technologies have significantly improved the output of manufacturing industry in China. However, the industry's position in the global value chain (GVC) has been challenged by digital transformation and efficiency. Since 2011, China's digital economy has experienced rapid expansion, impacting various subsectors in the manufacturing industry. Previous studies have examined the effect of digitization on the global value chain (GVC) in China's manufacturing industry using aggregate and disaggregate analyses. However, the isolated impact of hardware and software digital inputs on the manufacturing industry's GVC, and the sensitivity of digital inputs to production structure and efficiency are under explored. Using available data from 2007 to 2020 and 16 manufacturing subsectors, we examine the effect of hardware and software inputs on GVC in China's manufacturing sector. The results from the benchmark and fixed effect regression models show that digital inputs significantly contribute to the length of forward value chain, which interacts with total factor productivity to positively influence the GVC in the manufacturing industry. However, the disaggregate analysis shows that the input of digital hardware promotes GVC in the manufacturing industry. Similarly, digitization inputs significantly increase the GVC of China's technology- and capital-intensive industries, implying that digitization inputs extend the length of the forward value chain and improve China's position within the GVCs. Therefore, we offer some policy suggestions based on the empirical findings.

Keywords: digitization inputs, manufacturing industry, global value chain, China.

1. Introduction

The extensive use of information and communication technologies (for e.g. 5G, cloud computing, big data, and artificial intelligence) has effectively promoted cross-border integration in different industries (Goldfarb & Catherine, 2019). Digital inputs have become the new driving force for transforming and upgrading the manufacturing industry in recent years. Reports on the Development of China's Digital Economy show that the scale of China's digital economy in 2023 reached 53.9 trillion Yuan, accounting for 42.8% of GDP (National Bureau of Statistics of China, 2024). Recently, the Chinese economy has witnessed a period of transformation in the manufacturing industry and a breakthrough at the low end of the value chain. Simultaneously, the economy is identifying ways to maximize the benefits of digital economy and realize digital production inputs. Similarly, the key motive lies in empowering the manufacturing industry to achieve the high-end of the global value chain division, which has become an important aspect of economic and structural transformation. In 2021, the value-added of China's high-tech and equipment manufacturing industries increased by 18.2% and 12.9%, respectively, implying that the digitization process has become a driving force behind China's manufacturing transformation (Qi & Ren, 2021).

Over the year, developed economies have dominated the GVC in the manufacturing industry, exercising considerable power and influence (Zhang & Dai, 2022). However, China's manufacturing sector holds a comparatively consistent position in GVCs with a simpler rather than a complex embedded position (Liu et al., 2022; Hou et al., 2022; Chen et al., 2022). The country's digital industrialization reached 8.4 trillion yuan in 2021, representing 7.3% of GDP and a yearly nominal increase of 11.9%. Similarly, economic transformation and progress are driven by digitization process (Zhao, 2017), and the use of digital technology has increased significantly (Dilyard et al., 2021), leading to integration of information and communication technology in the manufacturing industry. Nonetheless, the isolated effects of digitization inputs on the manufacturing industry remain contentious. Digitization process has gradually changed the traditional mode of international trade, helping China's manufacturing GVCs overcome time and space constraints (Zhang, 2024), reshaping the industrial division of labor, and integrating related industries into the GVCs (Qu, 2022). Furthermore, GVCs leverage emerging opportunities by expanding domestic demand in an evolving economic landscape to gain new competitive advantages. Hence, the benefits of international trade depend not only on comparative advantages but also on the distribution and pattern of the manufacturing sector's value chain and its efficiency in resource allocation (Rasiah et al., 2011). The deep-rooted integration of digitalization and manufacturing has become an important driving force for improving the GVC in the manufacturing sector (Wang & Liu, 2022).

The relationship between digitization inputs and GVC in the manufacturing sector has received significant attention from empirical researchers. Specifically, Yu and Fang (2022) found that the digital-

induced manufacturing process influences high- and middle-income countries, and its impact on the GVC position is significant**.** Yang and Zheng (2023) used production length to portray the GVC position and found that the digital economy extends the length of the GVC, deepens the GVC division and resilience, and strengthens its stability over time. The digital economy penetration index constructed by Qi and Ren (2021) matches the digital intensity of medium- and high-tech industries across several dimensions. The authors pointed out that the penetration of the digital economy improved the GVC position of the country. Accordingly, the impact of digital infrastructure is higher and improves the GVC of medium- and low-technology manufacturing industries in the region. Moreover, Zhang and Yu (2020) screened digital economy elements and optimized digital economy indices and found that digital inputs enhance the GVC position of enterprises through increased productivity and innovation. Similarly, Xiang and Tian (2022) argued that the role of manufacturing digitization in enhancing the GVC position is mainly through the inputs of digital transactions and digital infrastructure, and that the effect of manufacturing digital inputs on the GVC position of developing countries is positive and significant for labor-, capital-, and technology-intensive industries. The above highlighted studies have identified different specifications and presented interesting empirical findings. However, majority of these studies are silent on the heterogeneous characteristics of the industry, influence of various types of digital inputs, and structural composition of the manufacturing industry.

Although China has surpassed many developed and developing economies in terms of economic growth, it still faces specific domestic economic challenges, partly due to influences such as trade protectionism, and the demand for Chinese products in the global market has faced restrictions (Kirton & Wang, 2023). Additionally, the inflow of advanced factors and the country's capacity to access cutting-edge technologies, particularly high-tech products, have affected China's economic dynamics. However, the disruptions and restructuring of GVCs due to the pandemic have added another layer of complexity and concern to the manufacturing industry (Ni & Tian, 2023). Specifically, Guo et al. (2023) quantify the effect and the rate of digitalization at the sectoral level in China from the perspective of production using the Inter-Country Input–Output (ICIO) accounting framework, which accounts for digitization in manufacturing industries through value chains. The results indicate that digitization process has developed rapidly in China and has become an important path for the transformation and upgrading of the manufacturing industry. This has been confirmed earlier by Chen and Xiaoxia (2018) using different data and approach to input-output analysis. In Spain, Añón Higón et al. (2025) examine the empirical link between the adoption of digital technologies and firms' participation in GVCs, and the channels through which this connection operates. The findings suggest that digitization is a key driver of GVC participation, both through a direct effect and an indirect effect resulting from enhanced productivity. However, building on the analyses of Añón Higón et al. (2025) and Guo et al. (2023), the

novelty of this study lies on isolating the impact of digital hardware and software inputs on manufacturing industry's GVC, as well as the sensitivity of the inputs to production structure and efficiency in capital- and technology-intensive segments of the manufacturing industry.

China's rapid integration into the GVC division is linked to its development strategy and the evolution of international GVC. Thus, China's manufacturing industry has been positioned and often participates in GVCs through lower-end embedded processes. But with the development of the digital economy and digital innovations, the country's manufacturing industry can transform low-end embedded GVCs into high-end embedded GVCs. Against the backdrop of the response of manufacturing GVCs to digitization inputs, this study isolates the effects of digitization inputs on GVCs in China's manufacturing industry based on disaggregate and heterogeneous analyses. Consequently, this study seeks to answer the following research questions: How do digitization inputs drive GVCs in China's manufacturing industry? How does industry heterogeneity influence the effect of digitization inputs on GVCs in the manufacturing sector? What are the transmission channels that moderate the impact of digitization inputs on the structure of manufacturing GVCs? The study answers these empirical questions using historical data from 2007 to 2020, 16 manufacturing subsectors, and employs robust and fixed effect regression models. We found that digital inputs significantly contribute to the length of the forward value chain in manufacturing. However, the total productivity of moderate digital inputs positively impacted the GVC of the manufacturing industry. Accordingly, the disaggregate analysis suggests that digital hardware inputs promote GVC in manufacturing. Structure-based analysis found that digitization inputs exert a significant positive impact on the GVC of technology- and capital-intensive industries.

Furthermore, this study contributes to the extant literature in the following ways: (1) We disaggregate and isolate the core industries of the digital economy, classified by the National Bureau of Statistics as the basis, and incorporate high-density sectors in the digital economy into the digital inputs in the empirical analysis. This approach can improve the precision of measuring changes in China's manufacturing industry's GVC position. (2) The study focused on the production structure and complexity of Chinese industries based on the length of the forward production in the manufacturing value chain. This approach adds supplements to the empirical context of the manufacturing industry's position in the GVC. (3) The study further extends the heterogeneity analyses through capital- and technology-intensive industries, and the impact of the sensitivity of digitization inputs to production structure and efficiency on manufacturing GVC. Finally, we utilized updated data from the OECD's Inter-Country Input-Output (OECD-ICIO) database to capture the dynamics of digitization inputs and GVCs in a rapidly developing manufacturing industry. The rest of the paper is organized as follows: Section 2 presents a review of related literature, theoretical foundation and research hypotheses; Section

3 presents the methodology for measuring digitization inputs and manufacturing GVCs; Section 4 provides insights into empirical modeling and specifications; Section 5 presents the empirical results and discussion of findings; and Section 6 presents the conclusions.

2. Literature review, theoretical foundation and hypotheses development

2.1. Literature review

In recent years, the connection between digitization and global value chains has received significant attention from theoretical and empirical researchers. Zhang et al. (2022) examined the impact of manufacturing digitization on the GVC position and found that digital transformation positively impacted GVC length and participation in China's manufacturing industry. Following the same line of argument, Chen and Yang (2021) found that the digital economy significantly improves the value chain in the manufacturing industry. Based on data from China's manufacturing industry, Wei (2023) used the consumption coefficient of the digital economy and the degree of complete dependence to examine the effect of digitization on GVC. The finding suggests that the digital economy enhances the GVC position of manufacturing industry, and there is evidence of industry heterogeneity. Guo and Wu (2022) argued that the digital-driven GVC of manufacturing and service industries paved the way to break through the low-end segment of China's GVC. From another perspective, Liu and Liu (2023) argued that digital technologies are conducive to promoting the relative position of China's GVC, especially in capital-intensive industries. Specific to the manufacturing industry, the literature uses aggregate digitization input measures and ignores the isolated impact of hardware and software (service) input on the GVC of the manufacturing industry in China. A strand of existing studies has focused on the digital transformation of micro firms as a measure of the digitization process (see Zhai et al., 2022; Jafari-Sadeghi et al., 2021; Qi & Song, 2024). Others have used the digital economy at the macro provinces and cities level (Zhang et al., 2022; Li & Wang, 2022). However, Gao et al. (2024) concentrated on industrial digitization and utilized the intermediate inputs of global computer manufacturing and information services to industry sectors in China. However, there is still a gap in quantifying and analyzing digitization inputs from the core manufacturing industry. Based on the OECD-ICIO data, we quantify and disaggregate the sources of digital inputs (hardware and software) and further investigate their impact on the manufacturing GVC in China.

On the heterogeneous impact of the digitization process and the emphasis on the impact of the digital economy on the development of industries, researchers have increasingly focused on the relationship between the digital economy and Global Value Chain (GVC) strategy (Loonam & O'Regan, 2022). Accordingly, the digital economy represents a new form of economic and social development, following agricultural and industrial economies. The advent of digital technologies has fundamentally transformed

production process and GVCs in the manufacturing sector. These digital technologies are poised to usher in new era of transformation and innovation, offering substantial growth and opportunities for GVCs (Banga, 2022; Parteka et al., 2024). On the one hand, enterprises use artificial intelligence to reduce labor costs and carry out repetitive production tasks through automated processes (Gao & Wang, 2020). However, these technologies can effectively deal with large-scale, repetitive, and intensive production tasks, thus enabling people to complete their tasks more efficiently and increasing the risk of layoffs among low-skilled laborers. The integration of artificial intelligence can reduce the labor costs of enterprises and improve their productivity (Lv et al., 2023). Further evidence shows that industrial automation replaces low-skilled labor and increases the value of the production process in the manufacturing industry's GVC (Li et al., 2020, 2023). While on one hand, digitization inputs are expected to replace a significant proportion of workers which may lead to structural unemployment (Dengler & Matthes, 2018; Acemoglu & Restrepo, 2020), on the other hand, they can also create new employment opportunities (Acemoglu & Restrepo, 2018).

From the foregoing, the link between digital technologies (inputs) and macroeconomy has received significant empirical attention from researchers. However, there remains a gap in the literature on the empirical understanding of how disaggregated digital inputs can impact GVC strategy in the manufacturing industry, as well as the heterogeneous and transmission channels through which digitization inputs influence manufacturing GVC in China. Considering the trends of digital transformation, a report by the China Information and Communications Technology Academy (ICTA) shows that China's digital input value was CNY 41 trillion in 2022, accounting for 33.9% of the GDP and 81.7% of the digital economy. Similarly, the penetration rates of digital economic activities in the primary, secondary, and tertiary industries were 10.5%, 24.0%, and 44.7%, respectively (Gao et al., 2024). Therefore, based on the micro and industry background of the digitization process, this study empirically examines the impact of DI on the GVC of the manufacturing industry in China, thus providing insights into how the isolated digital input impacts the GVC strategy in heterogeneous manufacturing industries.

2.2 Theoretical Foundation and Hypotheses Development

2.2.1 Direct impact of DI on the GVC of manufacturing industry

Manufacturing digitization signifies the extent to which digital technologies and products are adopted across the manufacturing sectors, thereby facilitating a more efficient integration into global trade activities (Yang et al., 2021). The theory of comparative advantage suggests that productive sectors (manufacturing and industrial) are predominantly influenced by labor and capital in their integration into global trade activities. However, the advancement of digital technologies introduces new dynamics

within the GVC. Digitization, as a new driving factor, enables the industrial sectors to leverage information technologies, such as big data, analytics, AI, and the internet, to enhance their integration into the global trade market (Aljohani et al., 2022; Huang & Zhang, 2023). DI, characterized primarily by digital technology, serves as a significant catalyst for GVC upgrading in manufacturing. In the context of GVC trade, digital inputs facilitate production segmentation, offer a streamlined method for interfacing and sharing data online for global products, thereby creating opportunities for more industries to integrate into the production segment of the GVC (Rachinger et al., 2018; Luo, 2022; Niehoff et al., 2022). The evolution of DI also implies an increase in the availability of digital products and services, thereby expanding the potential for the manufacturing industry to integrate into the GVC (Gopalan et al., 2022). Based on the above analysis, we propose hypothesis 1 as follows:

H_1: Digitization inputs promote manufacturing industry's global value chains.

2.2.2 Heterogeneous effects of DI on manufacturing industry's GVC

Digitization inputs can promote output within GVCs heterogeneously. The positive effect of digitization inputs on GVC in manufacturing is stronger for technology-intensive sectors compared to labor- or capital-intensive sectors (Zhang & Yu, 2020). The rationale behind this assertion is that technology-intensive firms are better equipped to absorb and leverage advanced digital inputs for innovation and complex problem-solving, which are key for sustainable growth and productivity. Empirical evidence from China confirms that ID boosts GVC position more significantly for technology-intensive sectors (Qi & Ren, 2020). Similarly, the theoretical basis for this linkage is aligned to improving export technology complexity (ETC) and enhancing revealed comparative advantage (RCA). Initial adoption of DI may bring significant costs, risks, and organizational disruptions that can hinder GVC activities. However, once a critical mass of digitalization is achieved and absorbed, the opportunities and efficiencies created begin to dominate, leading to a net positive and accelerating effect. This U-shaped pattern has been observed in the context of European manufacturing firms, and a similar conclusion elaborates on how DI enhances a country's significance in the GVC network. Ultimately, the study proposed a second hypothesis based on the wide application of digital technologies, which may have heterogeneous effects on the GVC of the manufacturing industry.

H_2: Digitization inputs have heterogeneous effects on GVCs in the manufacturing sector.

2.3. Transmission channels linking digital inputs and manufacturing GVCs

Enhancing the level of digitization within the manufacturing sector facilitates scale and agglomeration effects, thereby reducing the transaction costs associated with factor mobility and improving resource allocation efficiency. Consequently, manufacturing enterprises are better positioned to secure additional resources for R&D investments, digitized operations, and other strategic initiatives.

This brings about competitive advantages and strengthening their position within the GVC division. The theoretical submission of Solow (1987) contends that computers do not alter the intrinsic value of productivity, suggesting that their impact on productivity is negligible. The phenomenon of large-scale IT investments failing to enhance efficiency has been termed a "productivity paradox," a concept that has prompted academic debates for many years (Brynjolfsson & Hitt, 1996). However, with the ongoing expansion and development of the digital economy, which is increasingly integrated with industrial development, scholars have recognized its significant role in enhancing economic efficiency and labor productivity (Guo & Luo, 2008; Guo & Luo, 2016). In this context, Dewan and Kraemer (2000) utilized panel data from 36 countries spanning 1985 to 1993, demonstrating that IT inputs substantially improved productivity in developed countries. Guo and Luo (2016) recognized the Internet as a vital element in boosting total factor productivity (TFP) in China. Lv, Gu, and Bao (2020) found that Chinese firms are replacing labor inputs and enhancing firm productivity to strengthen their involvement in global value chains (GVCs).

However, some studies have pointed out that a country's absorptive capacity for productivity affects its participation in GVCs. The stronger a country's absorptive capacity, the more conducive it is to the digestion and absorption of the spillover effects brought by the GVC to better participate in the high-end spectrum of the GVC. In contrast, if absorptive capacity is weak, it will be caught in the low-end production spectrum of the GVC, which has a crowding-out effect on productivity spillovers (Yu et al., 2019). Accordingly, Yu and Fang (2022) found empirical evidence that total factor productivity (TFP) has a positive moderating effect of digitization on the manufacturing industry to upgrade the GVC position; that is, the higher the TFP and digital inputs, the more conducive it is to increase the GVC of the manufacturing industry. Therefore, we formulated Hypothesis 3 based on the above background.

H_3: The interaction between digitization inputs and total factor productivity drives the manufacturing industry’s GVCs.

3. Measuring digitization inputs and global value chains in China’s manufacturing industry

3.1. Digitization inputs in China's manufacturing industries

Yu and Fang (2022) measure digitization investment in China’s manufacturing industry as the absolute indicator of "direct and full consumption coefficients", which are used to measure digitization investment in China’s manufacturing industry. The direct consumption coefficient does not fully account for digitization investment and does not fully reflect economic interactions among industries. In contrast, the whole consumption coefficient can reflect the industrial linkage effect of the digital industry among industries and can be measured using the following equation:

$$Digc_{it} = \sum_i A_{it} + \sum_{m=1}^{N} A_{im}A_{mt} + \sum_{m=1}^{N}\sum_{t=1}^{N} A_{im}A_{mt}A_{tl} \quad (3.1)$$

In Equation (3.1), from left to right, is the direct consumption of digital industry *i* by sector *t*, the first round of indirect consumption of sector *i* by sector *t* through sector *m*, and so forth. The representation in terms of a matrix of consumption coefficients can be computed as $Digc_{it}$= A + A2 + A3 + ... +Am. Regarding the selection of the digital core industry, we follow Qi and Ren (2021) and Calvino et al. (2018) to measure the "industry digital intensity classification" through five indicators: ICT industry investment, ICT intermediate product procurement, robot utilization, ICT experts, and online sales. However, Calvino et al. (2018) pointed out that the geographic coverage of the indicator dimensions varies, and that the selection of some indicators does not apply to every country. The selection of some indicators is limited by the appropriate conversion of relevant figures from existing or national sector classifications to the ISIC. Accordingly, we adopted the procedure of Huang and Zhang (2023) to screen the scope of suitable core industries through the classification of core industries for the digital economy published by the National Bureau of Statistics (NBS), based on the ISIC Rev4.0 industry classification. The list of the industry scope of digital inputs includes the digital and manufacturing industry (C26TC27), the digital product service industry (C33), the digital technologies application industry (J61TJ63), the digital factor driving (J58TJ60), and the digital efficiency enhancement industry (H53, K64TK65). Finally, we screened out digital industries based on medium and high technological intensity, and the range of core digital economy industries classified by the NBS and the industries in the input-output table of the OECD-ICOT database were matched to obtain seven core digital industries (see Table 3.1). Industries such as digital hardware and digital media are classified according to the nature of the digitized inputs. Owing to capacity level constraints, the measurement approach for digitization was ultimately selected as a direct consumption factor. Thus, because of data constraints and the lack of maturity of the splitting method, the analysis only considers the fully digitized input industries included in the OECD database.

Table 3.1 Division of industries related to digital elements

categorization	Industry type	ICIO code	International coding (ISIC Rev4.0)	Product name
digital hardware	Digital Product Manufacturing	D26	C26	Computer, electronic and optical equipment
		D27	C27	Electrical equipment
	Digital technology applications industry	D61	J61	Telecommunications
		D62T63	J62-J63	IT and other information services
digital media	Digital elements driving industry	D58T60	J58	publishing activity
			J59-J60	Film, video and television production, sound recording and music publishing activities, programming and broadcasting activities
	Digital Efficiency	D53	H53	Postal and courier activities

	Enhancement Industry			

Source: OECD database

3.2. Measuring the length of manufacturing GVCs

The length of the value chain (PL) serves as a crucial indicator of a GVC's role in the division of labor and spatial separation of production chains in which it is integrated. It delineates the progression of product development from the initial factor inputs to the final product's consumption, encompassing multiple stages throughout the production process. This metric reflects the proportion of economy's contribution in the GVC production division and the increasing number of production stages within the value chain. Hence, a more complex production process signifies stronger intersectoral linkages and greater stability of the economic structure (Ni, 2016).

The length of the value chain entails calculating the average number of stages of production for a sector from initial inputs to final consumption, as measured by a multi-regional input-output model, thus measuring the footprint of each industry's value-added (both upstream and downstream) of the GVC in each country (Wang et al., 2017a). The approach measures the number of times value-added is considered as the total output, how much gross output is induced by one unit of value-added, and the length of the value chain, which is the ratio of gross output to value-added. At the production stage, value-added is used to produce intermediate or final goods, which are part of the output. Therefore, calculating the length of the value chain requires using the number of stages in the production chain as a weight, and the total output can be obtained by weighing the value added generated by each sector in the number of production stages. Following Wang et al. (2017a), we calculate the value added by the sector and the total output separately. The value added of the sector is measured as

$$\hat{V}B\hat{Y} = \hat{V}\hat{Y} + \hat{V}AA\hat{Y} + \ldots = \hat{V}(1 + A + AA + \ldots\ldots)\hat{Y} \quad (3.2)$$

Accordingly, the total output is calculated as:

$$\hat{V}BB\hat{Y} = \hat{V}\hat{Y} + 2\hat{V}A\hat{Y} + 3\hat{V}AA\hat{Y} + \ldots = \hat{V}(1 + 2A + 3A + \ldots)\,\hat{Y} = \hat{V}(B + AB + AAB + \ldots)\hat{Y} \quad (3.3)$$

In Equations (3.2) and (3.3), $\widehat{\mathrm{V}}$ is the direct value-added coefficient matrix, A is the input coefficient matrix, $\widehat{\mathrm{Y}}$ is the final product consumption coefficient matrix, and$\mathrm{B} = (\mathrm{I} - \mathrm{A})^{-1}$ is the Leontief inverse matrix, and all the above are GN × GN type matrices.

Therefore, from the economic definitions and calculations described above, the length of the value chain (Production Length, PL) of an industry can be expressed as:

$$PL = \hat{V}BB\hat{Y} / \hat{V}B\hat{Y} \quad (3.4)$$

Furthermore, Wang et al. (2017b) categorized the value chain production length into forward and backward value chain lengths, respectively. The forward value chain length measures the distance between the sector's initial inputs and final consumption products, reflecting the distance between a

sector's products and its upstream production links. The forward value chain length is calculated by adding the elements of matrix PL in the direction of the row. The larger the index, the more production stages from the downstream end and the closer it is to the upstream end. The backward value chain length measures the distance between the sector's final consumption products and the upstream products, reflecting the distance between the products of a particular sector and downstream. The elements of the matrix PL in the column direction are added to obtain the length of the backward value chain based on the industrial linkage. The larger the index, the farther it is from the upstream end of production and the closer it is to the downstream. The forward value chain length is calculated as follows:

$$Plv = \hat{V}BBY/\hat{V}BY = \hat{V}BB\text{ɳ}'/\hat{V}B\hat{Y}\text{ɳ}' \quad (3.5)$$

The backward value chain length is calculated as follows:

$$Ply = VBB\hat{Y}\,VB\hat{Y} = \text{ɳ}\hat{V}BB\hat{Y}/\text{ɳ}\hat{V}B\hat{Y} \quad (3.6)$$

In Equations (3.5) and (3.6), Y =$\hat{Y}$ɳ', ɳ is a 1 × GN unit matrix, and V = ɳ$\hat{V}$, ɳ is a 1 × GN unit matrix. This calculation reflects the production complexity and position of the GVC division.

4. Empirical analyses and specifications

4.1. Empirical models

This study examines the impact of digital inputs on GVCs in the manufacturing industry. Furthermore, we split digital inputs into digital hardware and software inputs and built on Gao and Wang (2020) to estimate the following fixed-effect models:

$$PLv_{it} = \beta_o + \beta_1 Dig_{it} + \beta_2 control_{it} + m_{it} + e_{it} \quad (4.1)$$

$$PLv_{it} = \beta_o + \beta_1 Digp_{it} + \beta_2 control_{it} + m_{it} + e_{it} \quad (4.2)$$

$$PLv_{it} = \beta_o + \beta_1 Digs_{it} + \beta_2 control_{it} + m_{it} + e_{it} \quad (4.3)$$

PLv denotes the length of forward production in the manufacturing value chain, Dig denotes the level of digitization inputs, $Digp$ denotes digital hardware, $Digs$ denotes digital media, Control denotes control variables including foreign direct investment, number of firms in the sector, human capital, technological innovation, market size, and fixed assets, i denotes the manufacturing industry, t denotes the year, m is an industry fixed effect, and e is a random error term. The control variables were treated logarithmically to eliminate the problem of heteroscedasticity between scalars. The inputs to the manufacturing industry from various digital economic activities are measured according to the construction decomposition of digital input indicators, which are divided into digital hardware ($Digp$) and digital media input ($Digs$).

4.2. Variables definition and measurement

4.2.1. Dependent variable: Length of forward value chain production

In this study, the forward value chain production length (PLv) is the dependent variable used to

measure the degree of embedding of the global value chain in the manufacturing sector. The forward value chain production length indicator indicates the total output caused by one unit of value added to a product, that is, the number of production stages by an industry from the initial inputs to the final consumption. The higher the indicator, the more downstream production stages the industry. The closer it is to the upstream production link, the farther it is from the final consumption end, and the more complex the production structure.

4.2.2. Core explanatory variables - Digitization inputs

The impact of the digital economy on manufacturing GVC is mainly reflected in the digital part of the manufacturing industry (Zhang et al., 2021); that is, the value-added investment brought to the manufacturing sector by the basic sectors of the digital economy. Therefore, this study selects manufacturing digitization inputs (Dig) as the core explanatory variable, which is measured by the direct consumption coefficient of the digital economy industry in the input-output table.

4.2.3. Moderating variables

This study used TFP as a moderating variable and transmission channel through which digital inputs drive GVC in the manufacturing industry. To measure TFP, we follow Fare (1994), who utilized the Malmquist index and data envelopment analysis (DEA) to calculate the total factor productivity (TFP) of China's manufacturing industry and decompose it into technical efficiency ($Effch$) and changes in technological progress ($techch$). Following Deng et al. (2023) approach, the output index was selected as the total industrial output value above the scale, and the input index was selected as the total assets of the industry above the average scale, and the annual average number of employees. In addition, if the base year 2006 TFP = 1, then the 2007 TFP equals the 2006 TFP multiplied by the 2007 Malmquist productivity index. Technical efficiency ($Effch$) and technical progress ($techch$) are calculated using the same approach as for TFP.

4.2.4 Control variables

Foreign direct investment (FDI): Foreign enterprises are characterized by their large scale and high degree of professionalism, which significantly contribute to the integration of China's manufacturing industries into global value chains (GVCs). Foreign direct investment facilitates increased participation of China's manufacturing industries in GVCs. However, according to the theory of comparative advantage, foreign enterprises typically operate at the lower end of China's manufacturing value chain, thereby hindering the advancement of the manufacturing industry's division within the GVC (Xie, 2023). Some studies have also pointed out the heterogeneous impact of FDI on China's GVCs (see Wang & Lu, 2022; Yu & Zhang, 2018). In this study, we used the sum of foreign

capital to measure FDI in the manufacturing industry in China.

Number of enterprises in the sector (Num): The number of enterprises indicates the degree and intensity of market competition in the industry and how conducive the economic system is to achieve the production frontier and potential output (He, 2020).

Human capital (Hum): R&D investment is important for technological innovation and economic transformation. The growth of R&D investment can drive technological progress in the industry and advance the global value chain position (Geng & Bai, 2019). However, improving the industry's GVC position may lead to a decline in GVC participation over time (Xie, 2023). This study adopts the full-time equivalent of R&D personnel to measure human capital.

Technological Innovation (Tech): This study measures technological innovation using the number of industry-related patent applications. The number of industry patents reflects technological innovation, which is conducive to promoting the position of the manufacturing industry's global value chain to the high end (Tu & Gong, 2022).

Market size (MC): The higher the market demand, the deeper the degree of embedding in the global production network. Following Kong et al. (2022), we employed the primary business revenue of each industry to measure the market size of the manufacturing industry.

Fixed assets (cap): Digital transformation in the manufacturing industry requires substantial capital investment in digital equipment. China's manufacturing industries operate at the middle and lower ends of the GVC. To reduce production costs and achieve efficiency, the industry requires large-scale machinery and fixed assets to effectively transform the inputs into outputs. However, integrating digital inputs into China's manufacturing industry can improve its position in GVCs. Table 4.1 summarizes the variables' measurements and definitions, acronyms used for each variable, and data sources.

Table 4.1: Variables definition, measurement and data sources

Variables	Designation	Variable Definition	Measurement	Data Sources
Dependent variables	PLv PLy	Length of the forward value chain production Length of the backward value chain production	See Wang et al (2017)	UIBE database
Independent variable	Dig	Digitization inputs	Direct Consumption factor	OECD database
Moderating variable	TFP	Total factor productivity	Calculation of the Malmquist index using DEAP 2.1 software	The China Industrial Statistics Yearbook (China) National Bureau of Statistics (NBS)

Control variables	FDI	Foreign direct investment	The sum of foreign capital and capital from Hong Kong, Macao, and Taiwan (billion yuan)	(China) National Bureau of Statistics (NBS)
	Num	Number of enterprises in the sector	Number of enterprises in the manufacturing sector (number)	The China Industrial Statistics Yearbook
	Hum	Human capital	Full-time equivalents of industry R&D personnel (person-years)	The China Statistical Yearbook
	$Tech$	Technological innovation	the number of industry patent applications (number)	The China Statistical Yearbook
	$Scal$	Market size	Revenue from main operations (billions of dollars)	The China Industrial Statistics Yearbook
	Cap	Fixed assets	Industry fixed assets (billions of dollars)	The China Statistical Yearbook

Note: All abbreviations are defined earlier in the previous section.

4.3. Data sources and descriptive statistics

This study uses panel data from 2007 to 2018. Data on digitization inputs were obtained by matching ISIC Rev.4 with ICIO input-output tables to obtain seven Chinese medium- and high-density digital-intensive industries and calculate their direct consumption coefficients. Data on the production length of the value chain were obtained from the UIBE Database.[1] Data on the control variables were obtained from the China Industrial Statistical Yearbook, China Statistical Yearbook, and the National Bureau of Statistics.[2] The statistical properties of the variables included in the analysis are summarized in Table 4.2.

Table 4.2: Descriptive statistics of the variables

	(1)	(2)	(3)	(4)	(5)
Variable name	N	Mean	Standard deviation	Minimum	Maximum
PLv	192	5.210	1.237	3.420	7.321
Dig	192	0.0506	0.0944	0.0015	0.418
Digp	192	0.0491	0.0943	0.001	0.417
Digs	192	0.00154	0.00099	0.0001	0.0069
FDI	192	8.828	0.940	6.240	10.80
Num	192	9.779	0.764	7.490	11.02
Hum	192	11.26	1.237	7.189	13.34
Tech	192	9.447	1.464	4.673	12.23
Cap	192	9.097	0.799	6.711	10.59
Scal	192	10.51	0.792	8.124	11.74

Note: All acronyms are defined in the previous section.

5. Empirical results

[1] See http://gvcdb.uibe.edu.cn
[2] See https://www.stats.gov.cn/

5.1. Benchmark regression

Initially, heteroscedasticity was identified in the panel data using White's test. Consequently, this issue was addressed by employing robust, standard errors. The presence of multicollinearity among the data was assessed using the variance inflation factor (VIF) method. The results indicated that the mean VIF value was less than 5 and the maximum VIF value was less than 10, suggesting the absence of multicollinearity. To prevent the existence of pseudo-regression in the specified model, a unit root test was conducted on the data, and it was found that the explanatory variable (PLv) and market size did not pass the stationarity test. However, the first difference of the variables passed the stability and cointegration tests. Therefore, there is a long-run equilibrium relationship among the variables; hence, we estimated the benchmark regression model.

Table 5.1 reports the benchmark regression results examining the effect of digitization inputs and their subdivisions on the production length of the manufacturing value chain. In particular, the main explanatory variable in column (1) is overall digitization inputs, the main explanatory variable in column (3) is digital hardware inputs, the main explanatory variable in column (5) is digital media, and columns (2) and (4) are regressions with control variables added to columns (1) and (3), with industry fixed effects in all benchmark regressions. The empirical results in columns (1)–(4) are significant, indicating that the overall digital inputs and digital hardware inputs have a significant positive impact on the length of China's manufacturing forward value chain, which is conducive to lengthening the forward value chain of the manufacturing industries. Accordingly, the digital inputs of manufacturing industries promote China's GVC division position to the high end of the chain, corroborating Hypothesis 1. The empirical results in columns (3)–(5) examine the impact of the subdivision of digitization inputs on manufacturing GVCs and find that digital hardware inputs play a significant role in raising the manufacturing industry’s GVCs. In contrast, digital media inputs do not considerably promote GVC in the manufacturing industry. Impliedly, the segments of digital inputs have a heterogeneous impact on manufacturing GVCs, as digital hardware inputs positively drive China's manufacturing industry to the high-end position of the GVC, confirming Hypothesis 2.

However, as the effect of digital hardware input on the length of the value chain is positive and significant, it enhances the length of the value chain. The positive impact of digital hardware inputs on the manufacturing industry implies that the digitization process can strengthen manufacturing capacity and output. Similarly, digital transformation is phenomenal in upgrading the manufacturing industry and leapfrogging to the high-end of the GVC.

Table 5.1: Results of the benchmark regression

Variables	(1)	(2)	(3)	(4)	(5)
	PLv	PLv	PLv	PLv	PLv

Dig	3.051**	3.972**			
	(2.37)	(2.72)			
Digp			3.169**	4.175***	
			(2.46)	(2.97)	
Digs					-33.783
					(-1.30)
FDI		-0.260		-0.274	-0.282
		(-1.56)		(-1.65)	(-1.58)
Num		-0.256**		-0.255**	-0.208*
		(-2.62)		(-2.62)	(-2.13)
Hum		-0.073		-0.075	-0.084
		(-1.11)		(-1.15)	(-1.42)
Tech		-0.121**		-0.120**	-0.110**
		(-2.45)		(-2.46)	(-2.44)
Cap		0.472**		0.482**	0.612***
		(2.80)		(2.92)	(3.10)
Scal		0.059		0.060	-0.016
		(1.22)		(1.24)	(-0.42)
Constant	5.055***	6.853***	5.054***	6.872***	6.368***
	(77.43)	(4.87)	(79.80)	(4.91)	(5.58)
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observations	192	192	192	192	192
Number of I.D	16	16	16	16	16
R-Squared	0.049	0.162	0.051	0.167	0.109

Note: T-statistics in parenthesis, *** p<0.01, ** p<0.05, and * p<0.10.

5.2 Robustness tests

The empirical results above show that manufacturing digitization inputs play an essential role in upgrading the GVC in the manufacturing industry. To further confirm this empirical relationship, we conducted robustness tests to ensure the reliability of our benchmark regression results.

(1) We replace the length of the forward value chain production (PLv) with backward global value chain participation (Gvcpt_b) for the robustness tests. The explanatory variables were digitization inputs (Dig), digitization hardware inputs (Digp), and digital media (Digs). Columns (1)–(3) in Table 5.2 confirm a negative relationship between digitization inputs and backward global value chain participation, which indicates that digitization inputs significantly drive and upgrade China's manufacturing industry in the GVC position, confirming that the result of the benchmark regression is robust, and this aligns with Hypothesis 1. However, both digitization and digital hardware inputs are significant at the 1% level, and digital media at the 10% level, considering the backward GVC participation. In terms of the heterogeneous impact of the explanatory variables, the findings confirm Hypothesis 2, which states that the impact of digitization inputs on manufacturing industries' GVCs is diverse and heterogeneous.

(2) Replacing the length of forward value chain production (PLv) with the backward average value chain production length (APL-B) and adding control variables, the results are presented in columns (4)-

(6) of Table 5.2, which show that both digitization inputs (Dig) and digital hardware inputs (Digp) can enhance the backward average value chain production length. This implies that digitization inputs positively influence the production length of manufacturing industries in the GVC. In comparative terms, digital hardware inputs play a more significant role in the length of the backward value chain and are more conducive to improving the production length of the value chain than software inputs. However, digital media does not significantly impact the production length of the backward value chain, indicating that the subdivision of digital inputs exerts heterogeneous impacts on the length of the value chain in the manufacturing industry, thus confirming Hypothesis 2. Overall, the results of the benchmark regression are valid and robust.

Table 5.2 Robustness Tests using alternative measures of forward value chain production

VARIABLES	(1) Gvcpt_b	(2) Gvcpt_b	(3) Gvcpt_b	(4) APL-B	(5) APL-B	(6) APL-B
Dig	-0.607***			2.023**		
	(-4.16)			(1.80)		
Digp		-0.598***			2.043**	
		(-3.97)			(1.80)	
Digs			-8.481**			11.993
			(-1.94)			(0.51)
Control	Yes	Yes	Yes	Yes	Yes	Yes
industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	192	192	192	192	192	192
Number of I.D	16	16	16	16	16	16
R-squared	0.345	0.342	0.318	0.212	0.211	0.194

Note: T-statistics in parenthesis, *** p<0.01, ** p<0.05, and * p<0.10.

5.3. Endogeneity test

The endogeneity analysis in this study is mainly based on the possible bidirectional causality between the core explanatory variables and the explained variable. Controlling for as many factors as possible that affect the GVC position based on the benchmark regression model and adding an industry-fixed effect. Our specification attempts to control the endogeneity problem to some extent, owing to the possible reverse causality between digitization inputs and the GVC position of manufacturing industries. Accordingly, we adopted the approach of Yu and Fang (2022), who used the first-order lagged term of digitization inputs as the instrumental variable and tested the empirical relationship using two-stage least squares. The results are presented in Table 5.3. Column (1) shows the results of the first-stage least squares method, which shows that the lagged value of digitization inputs has a positive and significant effect on the current period's value. In other words, the instrumental variable is related to an explanatory variable. Column (2) reports the results in which the length of forward value chain production is considered an explanatory variable. The findings indicate no evidence of over-identification because the number of instrumental variables is equal to the number of endogenous

explanatory variables, indicating that the digitized first-order lagged term was exogenous.

The instrumental variable was then subjected to unidentifiable and weak instrumental variable tests, and the test results are presented in Table 5.3. The result of the unidentifiable test indicates the rejection of the null hypothesis that the instrumental variables are identifiable. Hence, the instrumental variables are identifiable. The weak instrumental variable test results reject the hypothesis of a weak instrumental variable, indicating that the selected instrumental variables are valid. The results show that neither the significance nor the sign of the coefficients of digitization inputs change after replacing the instrumental variables. Therefore, the robustness of the previous findings is further confirmed after considering the endogeneity analysis of benchmark regression models.

Table 5.3 Result of the endogeneity test

	(1)	(2)
Variables	Dig	PLv
Dig		3.459***
		(3.19)
LDig	1.005***	
	(51.73)	
Control	Yes	Yes
industry fixed effect	Yes	Yes
Constant	-0.003	9.214***
	(-0.65)	(5.96)
Observations	176	176
R-squared	0.995	0.536
unidentifiable test		
Kleibergen-Paap rk LM statistic.	47.845***	
weak instrumental variable		
Cragg-Donald Wald F-statistics	1.3e+04	
Kleibergen-Paap rk Wald F-statistics	2675.754	
Stock-Yogo test	{16.38}	

Note: T-statistics in parenthesis, *** p<0.01, ** p<0.05, and * p<0.10.

5.4. Transmission effects of TFP

To some extent, the level of productivity represents the phase and technological aspects of a country's economic development. It is an important indicator of the size and cost of digitization technology acquisition in a country's manufacturing sector. Considering that the impact of digitization inputs on the GVC position of the manufacturing industry may be affected by sector productivity, this paper introduces total factor productivity (Tfp) into the model from 2007 to 2018 (with 2006 as the base period). The total productivity of manufacturing industries is derived by calculating the Malmquist index through Deap software, which is further decomposed into technical efficiency ($Effch$) and technical progress ($Techch$). To estimate the moderating effect of TFP, we specified the following empirical model:

$$PLv_{it} + \beta_o + \beta_1 Dig_{it} + \beta_2 Tfp_{it} + \beta_3 Dig_{it} * Tfp_{it} + m_{it} + e_{it} \quad (5.1)$$

$$PLv_{it} + \beta_o + \beta_1 Dig_{it} + \beta_2 Effch_{it} + \beta_3 Dig_{it} * Effch_{it} + m_{it} + e_{it} \quad (5.2)$$

$$PLv_{it} + \beta_o + \beta_1 Dig_{it} + \beta_2 Techch_{it} + \beta_3 Dig_{it} * Techch_{it} + m_{it} + e_{it} \quad (5.3)$$

Table 5.4 presents the empirical results of the transmission effect of TFP as specified in Equations (5.1) - (5.3). The transmission variable in columns (1) and (2) is the total factor productivity (Tfp), while the transmission channel through which technical efficiency ($Effch$), moderate the effect of digitalization inputs on the GVCs of manufacturing industry is captured in column (3). Similarly, the moderating variable in column (4) is technical progress ($Techch$). Therefore, the empirical results suggest that the interaction terms of total factor productivity, technical efficiency, and digital inputs positively impacted the GVC of the manufacturing industry at the 1% level. This indicates that the positive moderating effects of total factor productivity and technical efficiency on digitization inputs drive the GVC division. The higher the sector's productivity and technical efficiency, the more conducive digitization is in promoting GVC in China's manufacturing industry. The economic rationale for the negative impact of total factor productivity on GVCs may be that the degree of a country's participation in GVCs depends on its absorptive capacity for domestic productivity. If a country's absorptive capacity is low, it cannot fully digest the total factor productivity effectively, and the spillover effect is applied to GVCs. As most of China's manufacturing industries are still in the middle and low-end production chain, they will have a crowding-out effect on productivity (Yu et al., 2019), which is not conducive to upgrading China's manufacturing industry's GVC position.

Table 5.4: Moderating effects of the total factor productivity (TFP)

	(1)	(2)	(3)	(4)
Variables	PLv	PLv	PLv	PLv
Dig	4.396***	5.009***	3.954**	3.918**
	(3.31)	(3.51)	(2.64)	(2.78)
Tfp	-0.701***	-0.512***		
	(-5.08)	(-3.89)		
Dig*Tfp		6.941***		
		(3.47)		
Effch			0.243	
			(1.41)	
Dig*effch			5.480***	
			(3.66)	
Techch				-0.599***
				(-3.49)
Dig*techch				0.341
				(0.32)
Constant	7.953***	7.839***	6.242***	6.809***
	(6.18)	(5.83)	(3.72)	(4.79)
Control	Yes	Yes	Yes	Yes
industry fixed effect	Yes	Yes	Yes	Yes
Observations	192	192	192	192
Number of I.D	16	16	16	16
R-squared	0.251	0.276	0.198	0.259

Note: T-statistics in parenthesis, *** p<0.01, ** p<0.05, and * p<0.10.

5.5. Heterogeneity Analysis

The heterogeneity analysis in this study was based on the industry level. A significant number of empirical studies suggest that the digital economy serves as a catalyst for GVCs in the manufacturing sector. We utilized digitization inputs to analyze the evolving dynamics of the manufacturing industry. Given the heterogeneous effects of digitization inputs across different knowledge-intensive sectors and the inability of certain industries to capitalize on digital opportunities, it is imperative to examine the impact of digitization inputs on the GVC division of labor within diverse knowledge-intensive industries. Consequently, this study utilizes the classification method proposed by Zhang and Yu (2020) to categorize manufacturing industries into labor-, technology-, and capital-intensive sectors (Table 5.5).

In capital-intensive industries, digitization inputs (Dig) and digital hardware inputs (Digp) both enhance the length of GVC production in the manufacturing industry, with impact coefficients of 6.4 and 9.7 percentage points, respectively. This indicates that digital hardware inputs (Digp) have a more significant impact on the manufacturing of GVCs. In technology-intensive industries, both digitization input (Dig) and digital hardware input (Digp) positively impact forward production length (PLv) at the 1% level of significance. This implies that digitization and digital hardware inputs enhance GVC competitiveness and position in the manufacturing sector. However, no significant relationship was found between digitization inputs and forward value chain length (PLv) in labor-intensive industries, indicating that digitization inputs do not significantly promote the GVC position of labor-intensive industries. More precisely, digitization inputs (Dig) can promote GVC upgrading in capital- and technology-intensive industries but do not significantly impact GVC upgrading in labor-intensive ones. The economic rationale for this empirical finding is that labor-intensive industries are labor-enabled and have cost advantages. In these industries, digital inputs lead to labor substitution, but this substitution does not compensate for the labor loss. In contrast, capital- and technology-intensive industries have lower labor costs per unit of output. Similarly, there are more technical opportunities to serve product and service markets, where digital elements such as big data, the Internet of Things, and artificial intelligence can be effectively utilized.

Table 5.5: Result of the heterogeneity analysis

	capital-intensive		technology-intensive	
Variables	PLv	PLv	PLv	PLv
Dig	6.395*		6.365***	
	(2.04)		(5.43)	
Digp		9.716*		6.469***
		(2.23)		(5.27)
Control	Yes	Yes	Yes	Yes
Constant	8.654***	8.316***	5.715**	5.852**
	(4.68)	(4.46)	(3.12)	(3.29)
Industry effect fixed	Yes	Yes	Yes	Yes
Observations	84	84	72	72
Number of I.D	7	7	6	6
R-squared	0.343	0.354	0.338	0.342

Note: T-statistics in parenthesis, *** p<0.01, ** p<0.05, and * p<0.10.

6. Conclusions

The integration of the digitization process into the manufacturing industry has significantly enhanced the competitiveness and performance of China's productive capacity and manufacturing position in the GVC. Our empirical analyses using the benchmark regression model suggest that digitization inputs positively drive the GVC and the length of the forward value chain in the manufacturing industry, thereby improving the capacity and production structure of the manufacturing industry. However, we reciprocate this finding using backward value chain participation and backward average production length to test its robustness. The results found evidence of an inverse relationship between digitization inputs and the length of backward participation in the manufacturing GVC. However, the heterogeneity analysis categorized digital inputs into digital hardware and digital media (software) inputs to isolate the impact of each on the GVC of the manufacturing industry. We found that digital hardware inputs co-move with the forward production length of the manufacturing industry. Similarly, digital media significantly influences the average production length in the manufacturing sector. The economic rationale behind these empirical findings can be explained on the premise that the role of digitization in China’s manufacturing industry, as well as its position in the GVC, cannot be overemphasized at both the aggregate and disaggregate levels. Moreover, digital hardware inputs are more effective than digital media in promoting GVCs in the manufacturing industry. Regarding industry heterogeneity, digital inputs exert a more substantial effect on technology- and capital-intensive industries than on labor-intensive industries.

Furthermore, the interaction between digitization inputs and total factor productivity significantly moderates and enhances the positive impact on the GVC of the manufacturing industry. Based on the transmission channel analysis, the impact coefficient of the interaction term was substantially higher after mediation/interaction with TFP. Accordingly, we decomposed TFP into technical efficiency and progress, and the results suggest that the interaction between digitization inputs and technological

efficiency is particularly significant and exerts a positive impact on the manufacturing industry's GVC in China. Consequently, these findings have policy implications for China and other emerging markets. Since the value added of China's manufacturing industries was US$4.86 trillion in 2021, accounting for 27.4% of China's GDP, this structural transformation of the Chinese manufacturing industry is to a larger extent attributed to embedded digital processes in manufacturing, and its position in the GVC has shifted from low-end production and assembly to mid- and high-end segments such as research and development and after-sales services. Similarly, the technological revolution has promoted the rapid development of the digital economy, and digital technology has been widely used to promote cross-border integration and innovation across industries. The integration of the digital economy and manufacturing industry enhances the position of manufacturing GVCs in the global economy.

However, the study contributed to both theoretical and empirical fronts. Theoretically, the study contributed to the theoretical submission of revealed comparative advantages in the manufacturing industry, by integrating the role capital and technology in the relationship between digitization inputs and manufacturing GVC. Also, the sensitivity of digital inputs to production structure and efficiency adds another layer of theoretical insights to understanding the effect of digitization on manufacturing industry's GVC. Empirically, the study provides insight into the isolated impact of hardware and software digital inputs on the GVC of the manufacturing sector. Accordingly, the analysis further provides clear understanding on the extent and length of forward value chain in the manufacturing industry, and the response of the manufacturing GVC to digital inputs in capital- and technology-intensive manufacturing sectors. Despite its comprehensive empirical assessment of the relationship between digitization inputs and manufacturing GVC, the number of manufacturing sectors used as cross section limits the study's reliability to generalize on the empirical findings. Similarly, the study did not examine the effect of digital inputs on GVC of the manufacturing sector across regions and products categories. Future studies can explore this connection based on production line and regional heterogeneity of manufacturing firms, using firm-level data.

Therefore, based on the above theoretical and empirical analyses, harnessing digital infrastructure and consolidation of the essential support can improve digital footprint in the manufacturing industry. Digital infrastructure and digital elements can consolidate information infrastructure, reduce production costs and risks, and promote large-scale investment. Thus, it is imperative to support digital technology projects, promote the deep integration of information networks in industrial sites, and encourage innovation in the real sector. Similarly, reinforcing technological breakthroughs is key to controlling and improving digital technology in the manufacturing industry. To provide a lasting impetus for the rise of GVC in China's manufacturing industries, there is a need to concentrate more on core digital technologies that serve as a driving force behind China's economic progress and competitiveness. Thus,

to fully utilize production factors in the manufacturing industry, it is pertinent to encourage innovation and promote technological diffusion between the digital sector and real economic activities. Finally, efficiency is key in the manufacturing process. The role of TFP in promoting industrial structure is further consolidated by the efficient utilization of resources. For digital technologies and R&D to consolidate GVC conditions, digital resource utilization and real-time monitoring can be used to optimize the manufacturing industry's GVCs.

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Informed Consent

The research does not require informed consent, as the analysis did not involve human participants. It used empirical analysis based on historical data published by financial institutions. The data is available upon subscription and does not require informed consent.

Conflict of Interest

The authors declared no conflict of interest and agreed to submit the manuscript for publication.

Data Availability

The data supporting this study's findings are sourced from different sources and are available as open access. They are from the China Industrial Statistical Yearbook, the China Statistical Yearbook, the National Bureau of Statistics of China (https://www.stats.gov.cn/) and the OECD database.