

Embedding Section of Digital Technology and Global Value Chain Position

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Based on the distance between digital technology input in the manufacturing industry and the final product, this study measures digital technology embedding section bias and employs cross-country panel data to study its impact on the Global Value Chain (GVC) position. The results show that, first, the impact of digital technology embedding section bias on the manufacturing industry's GVC position has a significant inverted U-shaped feature, and embedding digital technology in the midstream is more conducive to improving GVC position. Second, embedding digital technology in the midstream can amplify the effect of innovation boundary and capability expansion, cost reduction, and production network linkage strengthening, thereby effectively promoting the improvement of the GVC position. Third, further research shows that embedding digital technology in the midstream is more conducive to alleviating the import dependence of high-tech intermediate products and can more effectively improve the domestic value-added rate of exports and economic growth quality. The above conclusions have important policy implications for optimizing China's digital development strategy and promoting GVC position.

Keywords: digital technology, embedding section bias, GVC position, manufacturing, intermediate products

1. Introduction

Since the Fourth Industrial Revolution, digital technology's role in the evolution of the global value chain (GVC) division of labor has drawn widespread academic attention. While existing literature generally acknowledges that increased digital

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technology investment helps industries progress in GVCs, it overlooks whether this effect varies across different embedding section biases. Under this research paradigm, most studies assume that comprehensively applying digital technology across all manufacturing dimensions, perspectives, and chains will fully unleash its potential effects. Consequently, proposed GVC upgrading strategies often ignore the differentiated effects of digital technology embedding sections, potentially leading to ineffective policies and causing China to miss crucial opportunities to secure a leading position in the new technological revolution's international division of labor. Currently, the digital transformation of manufacturing is confronted with high costs and significant transition pains (Liu *et al.*, 2021). Optimizing the embedding sections of digital technology to fully unleash its potential is a critical measure to avoid missteps in digital transformation and accelerate the resolution of transition challenges. It is also a vital safeguard for enhancing transformation effectiveness and facilitating manufacturing's rapid ascent to higher GVC positions. In this context, this paper investigates the impact of digital technology embedding section bias on GVC division position, providing important insights for China to appropriately position its digital development strategy and accelerate its progress in international division of labor.

In recent years, the literature on digital technology has grown substantially. One strand of research focuses on identifying the degree of digital technology embedding. Tracing methodological evolution, academic circles and international organizations initially explored applications of national accounting (OECD, 2015) and value-added statistics (Knickrehm *et al.*, 2016) in measuring the digital economy's scale. Subsequently, index compilation methods gained popularity (Bai and Zhang, 2021), though their selected indicators primarily reflected digital technology development from the supply side, failing to establish scientific measurement approaches from technology users' perspective. Addressing this limitation, scholars developed identification methodologies using consumption coefficients or value-added contributions (Dai and Yang, 2022; Wang *et al.*, 2023), significantly improving measurement accuracy. Building upon these methodologies, academic research conducted in-depth analyses of China's digital technology development and its embedding levels across various industries. However, few studies have examined the digital technology embedding section bias. Although some scholars empirically observed uneven digital technology embedding levels across different industrial chain sections (Jiao, 2020), the lack of corresponding identification methods confined research on digital technology embedding section bias to superficial qualitative analyses. Another strand of literature examines the relationship between digital technology and GVC position. As a crucial component of digital technology, artificial intelligence (AI) draws significant attention for its positive effects (Acemoglu *et al.*, 2020). Scholars worldwide demonstrate that increased AI adoption optimizes resource allocation (Acemoglu and Restrepo, 2018) and enhances GVC position through cost

reduction and efficiency improvement (Liu and Pan, 2020). Informatization, as a concrete manifestation of digital technology embedding in industrial sectors, has been shown by Zhang and Wang (2020) to elevate GVC position, providing critical evidence for understanding digital technology's role. In recent years, scholars have continued to improve in measuring digital technology embedding levels and examining its impacts. Studies reveal that in-depth digital technology embedding in industrial sectors can enhance connectivity among GVC participants (Foster *et al.*, 2018), enable small and medium-sized enterprises (SMEs) to integrate into GVCs and gain division-of-labor benefits (Jouanjean, 2019), and improve a country's GVC position through cost reduction and human capital structure optimization (Qi and Ren, 2021; Li *et al.*, 2023).

In summary, existing literature primarily focused on examining how the level of digital technology embedding affects GVC position, failing to clarify the role and mechanism of the digital technology embedding section bias. This limitation hinders China's efforts to optimize its digital development strategy and accelerate the improvement of its GVC position. Furthermore, the absence of method for identifying the digital technology embedding section bias impedes empirical research on its relationship with GVC position. To address these gaps, this paper will identify the digital technology embedding section bias in manufacturing and conduct a theoretical analysis and empirical testing of its impact on GVC position. The contributions are as follows: First, this study advances research on the digital technology-GVC position relationship by shifting focus from merely examining embedding level to analyzing embedding section bias, thereby expanding the research scope while providing valuable insights for China's GVC position improvement. Second, by examining digital technology's spillover effects across upstream and downstream sectors when embedding in midstream production, we theoretically elucidate the impact mechanisms of embedding section bias on GVC position through innovation boundaries and capability expansion, cost reduction, and network strengthening, offering policy foundations for optimizing China's digital development strategy. Third, we develop a novel measurement approach for embedding section bias based on the distance between digital technology's industry input and final manufacturing products, contributing a practical analytical tool for examining industrial digital transformation patterns.

2. Method Construction

2.1. Measurement Method for Digital Technology Embedding Section Bias

This study follows the method by Antràs *et al.* (2012) and Chen *et al.* (2019) to quantify the digital technology embedding section bias in manufacturing, by measuring the distance between digital technology industry inputs and final manufactured products. In a closed economy framework, the output of the digital technology sector g

(Y_g) relates to domestic final demand for the sector (F_g), its intermediate input usage in manufacturing (Z_g), intermediate input usage in other sectors (L_g), and inventory variations (I_g) through the following identity:

$$Y_g = F_g + Z_g + L_g + I_g \quad (1)$$

Let d_{gj} represent the number of intermediate inputs from the digital technology sector g required by the manufacturing sector j to produce one unit of output, giving

$$Y_g - I_g - L_g = F_g + Z_g = F_g + \sum_{j=1}^N d_{gj}(Y_j - I_j - L_j) \quad (2)$$

N represents the number of manufacturing sectors. Considering that the products of the manufacturing sector j are often absorbed as intermediate inputs by other manufacturing sectors k, l , and so on, Equation (2) can be expanded as follows:

$$Y_g - I_g - L_g = F_g + \sum_{j=1}^N d_{gj}F_j + \sum_{j=1}^N \sum_{k=1}^N d_{gk}d_{kj}F_j + \sum_{j=1}^N \sum_{k=1}^N \sum_{l=1}^N d_{gl}d_{lk}d_{kj}F_j + \dots \quad (3)$$

The terms on the right side of Equation (3) represent distinct production stages where products from digital technology sector g are applied. Following Antràs *et al.* (2012), the digital technology embedding section bias can be measured by the average distance from these production stages to the final product:

$$PH_g = 1 \times \frac{F_g}{Y_g - I_g - L_g} + 2 \times \frac{\sum_{j=1}^N d_{gj}F_j}{Y_g - I_g - L_g} + 3 \times \frac{\sum_{j=1}^N \sum_{k=1}^N d_{gk}d_{kj}F_j}{Y_g - I_g - L_g} + 4 \times \frac{\sum_{j=1}^N \sum_{k=1}^N \sum_{l=1}^N d_{gl}d_{lk}d_{kj}F_j}{Y_g - I_g - L_g} + \dots \quad (4)$$

PH_g represents the embedding section bias of digital technology sector g in manufacturing. Following Antràs *et al.* (2012)'s approach, we linearize Equation (4) and further account for open economy conditions by incorporating digital technology imports and exports, yielding

$$PH_g = 1 + \sum_{j=1}^N \frac{d_{gj}(Y_j - I_j - L_j) + X_{gj} - M_{gj}}{Y_g - I_g - L_g} U_j = 1 + \sum_{j=1}^N \lambda_{gj} U_j \quad (5)$$

$$\lambda_{gj} = \left[d_{gj}(Y_j - I_j - L_j) + X_{gj} - M_{gj} \right] / (Y_g - I_g - L_g) \quad (6)$$

Here, $d_{gj}(Y_j - I_j - L_j) / (Y_g - I_g - L_g)$ represents the proportion of digital technology sector g 's products consumed by manufacturing sector j , U_j denotes the upstream degree of sector j , X_{gj} indicates the amount of domestic digital technology sector g 's products consumed by foreign manufacturing sector j , while M_{gj} represents the amount of foreign digital technology sector g 's products consumed by domestic manufacturing sector j . Referring to Antràs *et al.* (2012)'s research, this paper assumes that the proportion of X_{gj} in the export of domestic digital technology industry g and the proportion of M_{gj} in the country's imports from foreign digital technology industry g are equal to λ_{gj} , obtaining Equation (7)'s digital technology embedding section bias index:

$$PH_g = 1 + \sum_{j=1}^N \frac{d_{gj}(Y_j - I_j - L_j)}{Y_g - I_g - L_g - X_g + M_g} U_j \quad (7)$$

A higher value of PH_g indicates that manufacturing sectors tend to utilize products from digital technology sector g primarily in the upstream production stages, demonstrating an upstream-biased embedding section for digital technology sector g within manufacturing. Furthermore, following the classifications established by Liu *et al.* (2020) and Wang *et al.* (2023), this study categorizes three sectors as digital technology industries: Computer, Electronic and Optical Equipment (D26), Telecommunications (D61), and Information Technology and Other Information Services (D62T63). Using the OECD Inter-Country Input-Output (OECD-ICIO) tables, we subsequently identify each country's embedding section bias patterns for these three digital technology sectors within their respective manufacturing industries.

2.2. Measurement Methods for GVC Division Positions

Based on the value-added decomposition model constructed by the OECD-ICIO tables and Wang *et al.* (2013), the specific components of each country's export value-added are obtained. Following Koopman *et al.* (2010), we measure GVC position using Equation (8). Here, $GVC_PO_{i,t}$ represents the GVC position of country i 's manufacturing sector in year t , where $IV_{i,t}$ and $FV_{i,t}$ denote the indirect

domestic value-added and foreign value-added in country i 's manufacturing exports, respectively, while $TE_{i,t}$ indicates the total value-added in country i 's manufacturing exports. Higher values of $GVC_PO_{i,t}$ indicate a higher GVC position for country i 's manufacturing sector.

$$GVC_PO_{i,t} = \ln \left(1 + \frac{IV_{i,t}}{TE_{i,t}} \right) - \ln \left(1 + \frac{FV_{i,t}}{TE_{i,t}} \right) \quad (8)$$

3. Theoretical Analysis

Current theoretical frameworks primarily focus on how the degree of digital technology embedding affects GVC position without explaining whether its impact varies across different embedding section biases. In reality, midstream production stages constitute the core of manufacturing competitiveness (Chen *et al.*, 2019). Guiding digital technology embedding toward midstream sections not only strengthens innovation capabilities, cost advantages, and production network connectivity in these critical stages but also utilizes their pivotal role in connecting upstream and downstream sectors to amplify digital technology's positive effects throughout the entire industrial chain, thereby more effectively improving GVC position advancement. The specific mechanisms operate as follows.

First, amplifying innovation boundaries and capability expansion effects. Promoting innovation serves as the core strategy and fundamental driver for countries to establish technological advantages in GVCs and rise to favorable positions. As the critical production stage in manufacturing, the innovation capacity of midstream sections particularly constitutes the essential foundation for industries to build core competitiveness and dominate mid-to-high positions in GVCs. Midstream-biased digital technology embedding in manufacturing effectively reduces information transmission costs for enterprises in this section (Yoo *et al.*, 2012), which broadens their access to domestic and international demand knowledge, enabling midstream enterprises to promptly identify the latest market trends and accordingly position new innovation directions. It also facilitates the integration of external high-quality factors and diversified knowledge, alleviating knowledge constraints in technological development while lowering factor and technical barriers (Shen *et al.*, 2023), thereby helping midstream enterprises expand innovation boundaries and enhance innovation capabilities. Moreover, with digital technology embedding preferentially in midstream manufacturing stages, midstream enterprises can utilize the in-depth application of digital simulation technology to conduct feasibility pre-assessment

of innovation solutions, thereby minimizing R&D risks as much as possible while shortening development cycles and improving research efficiency. Particularly, the midstream-biased digital technology embedding model enables enterprises in this section to utilize the ease of data and knowledge sharing, facilitating the formation of innovation alliances that transform independent innovation into collaborative innovation, thereby significantly expanding innovation boundaries and strengthening innovation capabilities. On this basis, the expanded innovation boundaries and enhanced innovation capabilities in midstream sections will elevate the requirements for upstream raw material supply categories, quality, and technical specifications. This creates “demand-induced innovation” that pressures upstream enterprises to intensify R&D efforts and achieve constructive alignment with midstream enterprises’ innovation directions, forming synergistic forces for technological breakthroughs. Furthermore, the new technologies and knowledge accumulated by midstream enterprises can spillover to downstream enterprises through input-output linkages, facilitating downstream innovation. This extends midstream innovation advantages throughout the entire industrial chain, broadening manufacturing’s comprehensive innovation boundaries and capabilities. Ultimately, this amplification of innovation boundaries and capacity expansion effects drives more substantial improvement in manufacturing’s GVC position.

Second, amplifying cost-saving effects. The midstream section faces substantially higher production costs due to its elevated technical difficulty and complexity, compounded by its greater requirements for cross-regional production coordination, which intensifies distribution cost pressures. These factors compress manufacturing value-added output, representing a major constraint on GVC position improvement. Promoting midstream-biased digital technology embedding in manufacturing not only significantly improves cross-regional coordination efficiency to reduce distribution costs (Dana and Orlov, 2014) but also enables intelligent business process management that helps midstream enterprises develop optimal production planning. This approach simultaneously reduces manufacturing error rates (Brynjolfsson and McAfee, 2017) and enhances production resource allocation efficiency (Qi and Ren, 2021), thereby decreasing midstream cost inputs while expanding competitive advantages, effectively overcoming cost-related constraints on manufacturing value-added acquisition and GVC position improvement. Furthermore, the cost advantages achieved in midstream sections can reduce input costs for downstream enterprises through input-output linkages, enhancing final product competitiveness and enabling downstream enterprises to capture greater value-added. Simultaneously, reduced midstream costs incentivize production scale expansion, thereby increasing demand for upstream material supplies, which helps upstream enterprises lower production costs through economies of scale. These cost reductions then propagate back through midstream and downstream sections, creating a virtuous

cycle of cost savings. In this scenario, the cost-saving effects generated by midstream-biased digital technology embedding radiate and amplify across different production stages, becoming a powerful engine for reducing costs throughout the entire industrial chain and capturing product value-added. This mechanism creates an expanded value-creation space for manufacturing, providing stronger momentum for GVC position improvement.

Third, amplifying network linkage enhancement effects. As the midstream is the most pivotal section in manufacturing value chains that critically connects upstream and downstream sections, midstream-focused digital technology investment can reduce transaction costs in information communication, warehousing, and logistics (Goldfarb and Tucker, 2019), thereby deepening the specialized division of labor. Moreover, midstream-biased digital embedding facilitates the effective integration of fragmented external production resources, incorporating more enterprises as collaborative participants within the same production stage (Wang *et al.*, 2023). Through digital platform-enabled cooperative manufacturing models, this approach strengthens connectivity and collaborative production capabilities among midstream participants, creating reinforced production network linkages that ultimately elevate the supply capacity and quality of midstream sections. On this basis, midstream enterprises can effectively communicate with domestic and foreign markets based on digital scenarios, develop and accurately connect with the production needs of downstream enterprises, and, with the support of the above-mentioned supply capacity and quality improvement, help promote the local substitution of intermediate goods, internalize the original intermediate goods needs of downstream enterprises for foreign midstream enterprises, and link and strengthen the domestic production network from the perspective of backward association. Furthermore, improved midstream supply quality drives upstream enterprises to refine the division of labor and extend production chains to fully absorb diverse local comparative advantages to meet higher midstream requirements, reinforcing domestic production networks through forward linkages. Ultimately, this amplified network linkage enhancement effect establishes a robust domestic industrial foundation with tight connections and strong supply capabilities across all sections, creating optimal conditions for manufacturing GVC position improvement, leading us to propose Hypotheses 1 and 2.

Hypothesis 1: The impact of digital technology embedding section bias on manufacturing GVC position follows an inverted U-shaped pattern, with midstream-biased digital technology embedding being the most conducive for GVC position improvement.

Hypothesis 2: Midstream-biased digital technology embedding in manufacturing can maximize GVC position improvement by amplifying three key effects: innovation boundary and capability expansion, cost savings, and network linkage enhancement.

4. Empirical Results and Analysis

4.1. Econometric Models, Variables, and Data

This study examines the impact of digital technology embedding section bias on manufacturing GVC position. Based on the theoretical analysis above, we establish the baseline econometric model as follows:

$$GVC_PO_{i,t} = \beta_0 + \beta_1 PH_{ig,t} + \beta_2 PH_{ig,t}^2 + \beta_3 Controls_{i,t} + \mathcal{G}_t + \mathcal{G}_{ig} + \varepsilon_{ig,t} \quad (9)$$

Here, t denotes year, i represents country, and g indicates digital technology sector. $GVC_PO_{i,t}$ stands for the GVC position of country i 's manufacturing sector (measured by Equation 8), $PH_{ig,t}$ reflects the embedding section bias of digital technology sector g in country i 's manufacturing (measured by Equation 7), $PH_{ig,t}^2$ is the squared term, $Controls_{i,t}$ represents control variables, $\mathcal{G}_t$ and $\mathcal{G}_{ig}$ denote time and country-sector fixed effects, respectively, and $\varepsilon_{ig,t}$ is the random disturbance term. The empirical analysis covers 65 countries/regions from 2000 to 2018. Control variables include (1) Digital technology application level (*DIG*), measured by value-added share from three digital technology sectors in total manufacturing output, (2) Labor force (*L*), measured by log-transformed total workforce, (3) Trade openness (*OPEN*), represented by total trade-to-GDP ratio, (4) Economic development level (*ECD*), measured by log-transformed GDP per capita, (5) Tax burden (*TAX*), calculated as tax revenue-to-GDP ratio, (6) Manufacturing scale (*SCALE*), represented by log-transformed total manufacturing output, (7) High-tech export share (*GJS*), measured by high-tech exports as a percentage of manufactured exports, and (8) FDI intensity (*FDI*), calculated as net FDI inflows-to-GDP ratio. *DIG* data are calculated using the OECD-ICIO and Wang *et al.* (2013)'s value-added decomposition model, total output data come from the OECD-ICIO, and other variables are sourced from the World Development Indicator (WDI) database.

4.2. Baseline Regression

This study utilizes ordinary least squares for baseline regression analysis. The results in Table 1 demonstrate an inverted U-shaped relationship between digital technology embedding section bias and manufacturing GVC position, indicating that midstream-biased deep embedding of digital technology most effectively promotes GVC position improvement, which is consistent with Hypothesis 1. Current research reveals comparatively low digital technology embedding levels in China's midstream

manufacturing sectors (Jiao, 2020), which fails to address these sections' inherent disadvantages requiring digital empowerment and constrains digital technology's full potential in elevating GVC position. To maximize digital technology's positive effects, future digital development strategies should incorporate this inverted U-shaped pattern by encouraging comprehensive digital technology embedding in midstream manufacturing, thereby generating stronger momentum for GVC position improvement.

Table 1. Benchmark Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>PH</i>	0.7478*** (0.0982)	0.7234*** (0.0982)	0.6498*** (0.0943)	0.6403*** (0.0853)	0.6565*** (0.0844)	0.4914*** (0.0666)	0.4927*** (0.0667)	0.4739*** (0.0668)	0.4745*** (0.0654)
<i>PH</i> ²	-0.2654*** (0.0354)	-0.2566*** (0.0354)	-0.2302*** (0.0338)	-0.2285*** (0.0307)	-0.2329*** (0.0303)	-0.1741*** (0.0239)	-0.1745*** (0.0240)	-0.1666*** (0.0240)	-0.1662*** (0.0235)
<i>DIG</i>		0.6485*** (0.1271)	0.4829*** (0.1294)	0.8987*** (0.1189)	0.7089*** (0.1252)	0.3731*** (0.1151)	0.3831*** (0.1144)	0.2824** (0.1167)	0.2450** (0.1158)
<i>L</i>			0.0886*** (0.0079)	0.0307*** (0.0073)	0.0333*** (0.0071)	0.0209*** (0.0068)	0.0281*** (0.0069)	0.0240*** (0.0072)	0.0252*** (0.0072)
<i>OPEN</i>				-0.0745*** (0.0033)	-0.0704*** (0.0035)	-0.0704*** (0.0038)	-0.0662*** (0.0039)	-0.0663*** (0.0039)	-0.0649*** (0.0039)
<i>ECD</i>					0.0102*** (0.0025)	0.0173*** (0.0024)	0.0338*** (0.0050)	0.0422*** (0.0049)	0.0436*** (0.0049)
<i>TAX</i>						-0.1604*** (0.0145)	-0.1413*** (0.0155)	-0.1343*** (0.0153)	-0.1426*** (0.0150)
<i>SCARE</i>							-0.0170*** (0.0048)	-0.0235*** (0.0047)	-0.0240*** (0.0047)
<i>GJS</i>								-0.0127* (0.0073)	-0.0127* (0.0074)
<i>FDI</i>									0.0063*** (0.0018)
Constant terms	-0.5991*** (0.0652)	-0.5918*** (0.0651)	-0.3159*** (0.0667)	-0.3869*** (0.0603)	-0.3968*** (0.0596)	-0.2913*** (0.0479)	-0.2455*** (0.0504)	-0.2313*** (0.0502)	-0.2286*** (0.0492)
Time effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	3705	3705	3705	3699	3699	3396	3396	3213	3213
R ²	0.9256	0.9260	0.9288	0.9400	0.9405	0.9582	0.9584	0.9626	0.9628

Note: Robustness standard errors are reported in parentheses, with *, **, and *** indicating 10%, 5%, and 1% significance levels, respectively. The same applies hereinafter.

4.3. Endogeneity Test¹

To address potential endogeneity issues arising from reverse causality between digital technology embedding section bias and GVC position, this study utilizes a two-stage least squares approach with the following three instrumental variables. First, following Shi and You (2021), we calculate the cubic terms of the deviations between the digital technology embedding section bias index (and its squared term) and their respective mean values as instrumental variables (*IV-a*). Second, adopting Chen and Qin (2022)'s approach, we construct Bartik instruments using the shift-share method, initially computing the annual global mean (excluding the country itself) of digital technology embedding section bias HP_t , then determining its growth rate $GP_t = HP_t / L.HP_t$, with the resulting Bartik instrument being $IV = GP_t \times L.PH_{ig,t}$. After standardizing the *IV*, we use their first-order and second-order terms as instrumental variables for the current-period digital technology embedding section bias and its squared term, respectively (*IV-b*).

Third, to enhance the economic relevance of the Bartik instruments, we categorize annual samples into 10 groups (10th, 20th, ...90th percentiles) based on income per capita levels. Following the aforementioned methodology, we calculate growth rates of the digital technology embedding section bias means for each group (excluding the country itself), then multiply these rates by one-period-lagged embedding section bias values. After standardization, we use their first-order and second-order terms to construct an additional instrumental variable (*IV-c*). Income per capita is measured by GDP (2017 constant prices, PPP-adjusted) divided by employed population, with data from the WDI and Penn World Table. Economically, countries with similar income levels tend to share comparable digital technology and manufacturing development stages as well as comparative advantages, leading to analogous digital technology embedding section bias patterns. Therefore, *IV-c* exhibits significant correlation with the current domestic digital technology embedding section bias. However, since the construction of the *IV-c* instrumental variable is fundamentally based on the growth rates of the *PH* variable from other group countries, *IV-c* is unlikely to directly affect the domestic manufacturing sector's GVC position, thus ensuring the exogeneity of this instrumental variable. The test results show that there is no unrecognizable or weakly recognized problem of the above instrumental variables, and the coefficients of *PH* variables and square terms do not change significantly, indicating that the core conclusion of this paper is still valid under the condition of considering endogeneity.

¹ Due to space limitations, the text does not report the results of the endogeneity test and the robustness test methods and results, which are retained for future reference.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>Stage 1</i>	<i>Stage 2</i>	<i>Stage 1</i>	<i>Stage 2</i>	<i>Stage 1</i>	<i>Stage 2</i>	<i>Stage 1</i>	<i>Stage 2</i>
Explained variables	<i>PHHI</i>	<i>GVC_PO</i>	<i>R&D</i>	<i>GVC_PO</i>	<i>PATENT</i>	<i>GVC_PO</i>	<i>RDE</i>	<i>GVC_PO</i>
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	2301	2301	2793	2793	3012	3012	2385	2385
R ²	0.5918	0.9597	0.9602	0.9637	0.9435	0.9645	0.7659	0.9644

4.4.2. Analysis of Cost-Saving Mechanisms

This study utilizes the OECD-ICIO database to measure manufacturing cost inputs through input-output ratios, which comprehensively and intuitively reflect the cost inputs required per unit of manufacturing output in the form of intermediate inputs from domestic and foreign industries. Empirically, we use two proxy variables: the ratio of intermediate inputs to total output (*COST-a*) and the ratio of intermediate inputs to value-added output (*COST-b*). The test results are presented in Table 3, where the first-stage results demonstrate that midstream-biased digital technology embedding in manufacturing proves more effective in reducing cost inputs. Meanwhile, the second-stage results show that cost inputs have a significantly negative impact on GVC position, indicating that cost reduction helps expand manufacturing value creation space and is an important driving force for promoting GVC position. This demonstrates that midstream-biased digital technology embedding can maximize GVC position improvement by amplifying cost-saving effects.

Table 3. Results of the Test of the Cost-Saving Mechanism

	(1)	(2)	(3)	(4)
Explained variables	<i>Stage 1</i> <i>COST-a</i>	<i>Stage 2</i> <i>GVC_PO</i>	<i>Stage 1</i> <i>COST-b</i>	<i>Stage 2</i> <i>GVC_PO</i>
<i>PH</i>	−0.1180* (0.0662)	0.4293*** (0.0588)	−1.3099** (0.6458)	0.4324*** (0.0604)
<i>PH 2</i>	0.0428* (0.0235)	−0.1498*** (0.0211)	0.4237* (0.2278)	−0.1526*** (0.0218)
<i>COST-a</i>		−0.3831*** (0.0184)		
<i>COST-b</i>				−0.0322*** (0.0019)
Control variables	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes

	(1)	(2)	(3)	(4)
Explained variables	<i>Stage 1</i> <i>COST-a</i>	<i>Stage 2</i> <i>GVC_PO</i>	<i>Stage 1</i> <i>COST-b</i>	<i>Stage 2</i> <i>GVC_PO</i>
Country-industry effects	Yes	Yes	Yes	Yes
Sample size	3213	3213	3213	3213
R ²	0.9095	0.9675	0.9205	0.9672

4.4.3. Analysis of the Mechanism of Link Reinforcement in the Production Network

This study adopts the production length measurement method developed by Wang *et al.* (2017) to calculate domestic production steps using OECD-ICIO data, reflecting production network linkage intensity. We first measure forward domestic production length (*PLv*) and backward domestic production length (*PLy*) at the manufacturing sector level for each country. Higher values indicate more domestic production stages and tighter domestic production network linkages formed through the integration of local production factors. Using each sector's output share in total manufacturing output as weights, we then compute weighted sums of *PLv* and *PLy* to obtain forward domestic production length (*FLVC*) and backward domestic production length (*BLVC*) for each country's manufacturing sector. The total domestic production length (*LVC*) is measured by multiplying *FLVC* and *BLVC*. Table 4 presents the mechanism analysis results. The first-stage results show that midstream-biased digital technology embedding in manufacturing maximizes the improvement of forward, backward, and total domestic production lengths, thereby amplifying domestic production network linkage enhancement effects. Meanwhile, the second-stage results demonstrate that strengthened domestic production network linkages establish a robust domestic industrial chain foundation conducive to GVC position improvement. This indicates that guiding midstream-biased digital technology embedding in manufacturing will more effectively drive GVC position improvement by amplifying domestic production network linkage effects. These findings validate Hypothesis 2.

Table 4. The Test Results of the Linkage Strengthening Mechanism of the Production Network

	(1)	(2)	(3)	(4)	(5)	(6)
Explained variables	<i>Stage 1</i> <i>FLVC</i>	<i>Stage 2</i> <i>GVC_PO</i>	<i>Stage 1</i> <i>BLVC</i>	<i>Stage 2</i> <i>GVC_PO</i>	<i>Stage 1</i> <i>LVC</i>	<i>Stage 2</i> <i>GVC_PO</i>
<i>PH</i>	0.7239*** (0.1988)	0.4294*** (0.0618)	1.0237*** (0.2014)	0.3798*** (0.0612)	3.0801*** (0.6877)	0.3958*** (0.0607)
<i>PH 2</i>	-0.2226*** (0.0715)	-0.1524*** (0.0220)	-0.3417*** (0.0714)	-0.1346*** (0.0217)	-0.9902*** (0.2458)	-0.1409*** (0.0215)
<i>FLVC</i>		0.0622*** (0.0073)				

Explained variables	(1) <i>Stage 1 FLVC</i>	(2) <i>Stage 2 GVC_PO</i>	(3) <i>Stage 1 BLVC</i>	(4) <i>Stage 2 GVC_PO</i>	(5) <i>Stage 1 LVC</i>	(6) <i>Stage 2 GVC_PO</i>
<i>BLVC</i>				0.0925*** (0.0078)		
<i>LVC</i>						0.0255*** (0.0022)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes	Yes
Country-industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	3213	3213	3213	3213	3213	3213
R ²	0.9336	0.9640	0.9423	0.9655	0.9472	0.9651

5. Further Analysis

The import of core intermediate goods and key technologies once served as crucial external forces supporting the enhancement of China's manufacturing competitiveness and export capacity. However, current blockade measures targeting these intermediates and high-tech products have now become political tools and sanction instruments utilized by certain countries to restrict the improvement of China's manufacturing competitiveness and GVC position. Consequently, imports of intermediate goods, particularly high-tech intermediates, have transformed into channels for external risk exposure, objectively exposing manufacturing to the risk of being locked into low-profit, low-value-added production stages, thereby hindering the high-quality development of foreign trade and the national economy. Therefore, this study will further examine how digital technology embedding section bias affects intermediate goods imports, domestic value-added ratio in exports, and economic growth quality to determine whether midstream-biased digital technology embedding can help manufacturing overcome these challenges, thereby providing valuable insights for China's high-quality development in foreign trade and economy.

5.1. Digital Technology Embedding Section Bias and Intermediate Goods Imports

This study utilizes OECD-ICIO data to calculate manufacturing intermediate import dependence (*IPD*) as the ratio of import intermediates to total intermediate consumption. Following Chen *et al.* (2021), we measure intermediate import sophistication and construct high-tech intermediate import dependence (*HIPD*) by

connecting this measure with the *IPD* variable. The results in Table 5 reveal a U-shaped relationship between digital technology embedding section bias and both intermediate import dependence and high-tech intermediate import dependence. This indicates that promoting the embedding of digital technology in the midstream stages in the manufacturing industry is more conducive to strengthening innovation advantages, cost competitiveness, and production network linkages in intermediate production stages. Consequently, it enhances domestic intermediate production capacity and self-sufficiency rates, thereby significantly reducing dependence on intermediate imports, particularly high-tech intermediates. During economic globalization, China's manufacturing sector opted for importing rather than domestic production as a shortcut to rapidly enhance competitiveness and address intermediate supply challenges. This approach has created significant external dependencies for numerous enterprises in intermediate goods, not only allowing foreign suppliers to capture substantial manufacturing profits but also increasing domestic vulnerability to supply disruptions and technological bottlenecks. These findings provide valuable insights for China to utilize optimal digital technology embedding sections, achieve self-sufficiency in intermediate goods (especially high-tech intermediates), reduce import dependence, and, consequently, narrow risk transmission channels in the future.

Table 5. Results of the Study on Embedding Bias and Intermediate Imports

Explained variables	(1)	(2)	(3)	(4)
	<i>IPD</i>		<i>HIPD</i>	
<i>PH</i>	-0.7409*** (0.1245)	-0.5934*** (0.0915)	-0.8002*** (0.1473)	-0.6366*** (0.1120)
<i>PH 2</i>	0.2571*** (0.0453)	0.2044*** (0.0335)	0.2815*** (0.0531)	0.2240*** (0.0404)
Control variables	No	Yes	No	Yes
Time effect	Yes	Yes	Yes	Yes
Country-industry effects	Yes	Yes	Yes	Yes
Sample size	3705	3213	3705	3213
R ²	0.9201	0.9605	0.9225	0.9596

5.2. Digital Technology Embedding Section Bias and Domestic Value-Added Ratio in Exports

This study utilizes the value-added decomposition model proposed by Wang *et al.* (2013) with OECD-ICIO data to calculate total domestic value-added share in manufacturing exports (*DV*), foreign-absorbed domestic value-added share (*DVA*), domestic value-added share in intermediate exports (*DV_INT*), and domestic value-added share in final goods exports (*DV_FIN*). As Table 6's results demonstrate, midstream-biased digital technology embedding proves more effective in elevating

domestic value-added ratios, enabling countries to capture greater export benefits. As China's manufacturing sector ascends to higher GVC positions, it frequently encounters technological blockades from developed countries and "profit erosion" through price suppression. These challenges simultaneously hinder technological progress through imitation while undermining self-funded R&D capabilities from profit accumulation, potentially trapping production in low-value-added stages. These findings suggest that promoting midstream-biased digital technology embedding can better counter developed countries' containment strategies by enhancing endogenous innovation capacity, cost advantages, and domestic production networks across the entire industrial chain. This approach enables a maximized capture of trade value-added benefits in GVC division of labor while avoiding low-value-added lock-in effects.

Table 6. Research Results on Embedding Sections Bias and Domestic Value-Added Ratio in Exports

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Explained variables	<i>DV</i>		<i>DVA</i>		<i>DV_INT</i>		<i>DV_FIN</i>	
<i>PH</i>	0.5671*** (0.1088)	0.4237*** (0.0757)	0.5645*** (0.1073)	0.4184*** (0.0750)	0.5339*** (0.1126)	0.3747*** (0.0801)	0.6290*** (0.0968)	0.5189*** (0.0759)
<i>PH 2</i>	-0.1973*** (0.0392)	-0.1442*** (0.0270)	-0.1955*** (0.0386)	-0.1420*** (0.0267)	-0.1865*** (0.0408)	-0.1290*** (0.0288)	-0.2185*** (0.0350)	-0.1757*** (0.0270)
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Time effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	3705	3213	3705	3213	3705	3213	3705	3213
<i>R</i> ²	0.9325	0.9645	0.9306	0.9628	0.9265	0.9578	0.9393	0.9642

5.3. Digital Technology Embedding Section Bias and Economic Growth Quality

This study measures economic growth quality across three dimensions: growth rate, stability, and efficiency. First, economic growth rate (*EG*) is represented by GDP growth rates from the WDI database. The second is economic growth stability (*STAB*), which first uses the HP filter method to obtain the fluctuation component of each country's GDP and then calculates its five-period rolling standard deviation, which is taken as the reciprocal as a proxy variable for economic growth stability. The third is production efficiency. First, the overall production efficiency (*EFFI*) is reflected by multiplying the productivity of labor factors, capital factors, and other factors, in which the productivity of labor factors is expressed as the ratio of output to the number of employees, the productivity of capital factors is expressed as the ratio of output to capital stock, and the remaining factor productivity is expressed by the total

factor productivity calculated based on the LP method, and the data come from the WIOD Socio-Economic Account database. Second, this paper also uses the total factor productivity data provided by the Penn World Table database to measure production efficiency (*TFP*). In addition, based on three indicators, economic growth rate (*EG*), stability (*STAB*), and efficiency (*TFP*), this paper uses the entropy method to measure the overall economic growth quality (*ZB*) of a country. The results of the regression based on each variable are shown in Table 7.

Table 7. Research Findings on Embedding Sections Bias and Economic Growth Quality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Explained variables	<i>EG</i>		<i>STAB</i>		<i>EFFI</i>	<i>TFP</i>	<i>ZB</i>	
<i>PH</i>	0.9569*** (0.2327)	0.9175*** (0.2591)	0.9849*** (0.3369)	1.5717*** (0.3651)	0.8934* (0.5098)	0.4473*** (0.1510)	0.4466*** (0.1048)	0.6080*** (0.1114)
<i>PH 2</i>	-0.3294*** (0.0826)	-0.3138*** (0.0912)	-0.3375*** (0.1224)	-0.5386*** (0.1334)	-0.3439** (0.1738)	-0.1551*** (0.0540)	-0.1586*** (0.0380)	-0.2090*** (0.0404)
Control variables	No	Yes	No	Yes	Yes	Yes	No	Yes
Time effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	3705	3213	3705	3213	1806	3147	3705	3213
R^2	0.5471	0.6168	0.5172	0.5642	0.8849	0.7574	0.5774	0.6182

The results show that midstream-biased digital technology embedding in manufacturing can greatly improve economic growth, stability, and production efficiency to improve the quality of a country's economic growth more effectively; the overall economic growth quality is further taken as the explained variable, and the same conclusion is obtained in this paper. According to the empirical results of the above-mentioned digital technology embedding section bias and intermediate goods import and export domestic value-added rate, it can be seen that the manufacturing sector is biased toward the midstream sections embedding digital technology, which can increase the contribution of exports to the growth of the total economy by effectively improving the domestic value-added rate of exports and curb the transmission of external risks as much as possible by effectively reducing the import of intermediate goods, which is conducive to the maximization of national economic growth, growth stability, and efficiency and is an important starting point for improving the quality of economic growth in China in the future.

6. Conclusions and Policy Implications

This study identifies digital technology embedding section bias in manufacturing

by measuring the distance from digital technology sector inputs to final manufactured products and examines its impact on GVC position and underlying mechanisms. The key findings are as follows: First, digital technology embedding section bias exhibits an obvious inverted U-shaped relationship with manufacturing GVC position, and encouraging the manufacturing sector to embed digital technology in the midstream sections is more conducive to improving the GVC division of labor. Second, the mechanism analysis shows that midstream-biased digital technology embedding can promote the greater rise of GVC position by amplifying the innovation boundary and capacity expansion effect, the cost saving effect, and the production network link strengthening effect and then form the above-mentioned inverted U-shaped impact. Third, further research finds that promoting midstream-biased embedding can also help to alleviate the import dependence of intermediate goods, especially high-tech intermediate goods, and more effectively promote the improvement of the domestic value-added rate of exports and the quality of economic growth, which can become a powerful starting point for promoting the high-quality development of foreign trade and the national economy.

This study provides theoretical and empirical evidence for China to optimize its digital development strategy, accelerate the progress in manufacturing GVC position, and achieve high-quality development. The findings offer clear policy implications: China should follow the inverted U-shaped impact of digital technology embedding section bias on GVC position by guiding manufacturers to deeply embed digital technologies in midstream production stages. First, priority should be given to implementing additional tax deductions for digital transformation expenses in midstream enterprises engaged in core component manufacturing and equipment supply. The intensity of preferential loan rates, tax reductions, and subsidies should be linked to enterprises' digital transformation plans and their respective production stages, significantly enhancing incentives for midstream enterprises' digital transformation. Second, efforts should be put to improve digital infrastructure construction, increase funding and personnel investment in digital technology R&D, and encourage digital technology enterprises to strengthen the development of foundational and cutting-edge technologies. This will establish an independent, controllable, and robust digital technology industrial system, enhancing its capability to support digital transformation in midstream high-complexity production stages. Third, it is also important to enhance inter-regional economic openness and establish tightly connected, stable domestic industrial chains to lay a solid foundation for transmitting midstream digital empowerment effects to upstream and downstream sectors. Finally, local governments and industry associations should be encouraged to continuously monitor manufacturing's digital technology embedding section bias, using this data to optimize digital policies and maintain high digital technology embedding levels in midstream stages over the long term, creating strong momentum for sustained GVC position improvement.

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