Research on the Promotion of High-Quality Development of Manufacturing Enterprises in Tai'an City by Digital Productivity

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Abstract: Drawing on the theoretical core of digital productivity, this research analyzes how digital productivity affects the high-quality development of manufacturing enterprises. Based on economic theories, this study first formulates a research hypothesis, then empirically tests the theoretical proposition using a sample of manufacturing enterprises in Taian City from 2011 to 2022. Specifically, this study constructs an indicator evaluation system for digital productivity and high-quality development in manufacturing, measures their development indices, and employs a two-way fixed effects model to empirically test the theoretical mechanisms. The following conclusion has been obtained through research: Improving the development level of digital productivity is conducive to promoting the high-quality development of manufacturing enterprises in Tai'an. This paper, leveraging the research conclusions mentioned above, comes up with targeted strategy proposals for propelling the high-quality progress of Tai'an's manufacturing enterprises.

Keywords: Digital Productivity; The Manufacturing Industry in Tai'an City; High-quality Development

1. Introduction

The concept of digital productivity orginfrom scholars' in-depth exploration of the connotation of new-quality productivity [1], and its logical structure and core elements continue the essential thread of new-quality productivity. Digital productivity is driving the high-end, intelligent, green and service-oriented upgrading of traditional manufacturing industries. By 2027, the development level of the high-end, intelligent, green and integrated development of China's traditional manufacturing industry will be significantly improved, effectively supporting the maintenance of a basically stable proportion of the manufacturing industry, and further consolidating and enhancing its status and competitiveness in the global industrial division of labor. Thus, an exploration of the ways in which digital productivity enables high-standard development of the manufacturing enterprises holds significant value. It provides theoretical support and practical directions for the manufacturing enterprises as it navigates the unbalanced development strategy adjustment. It can also offer new perspectives and methods for promoting the development of new-quality productivity, thus possessing strong theoretical and practical significance.

In recent years, Tai'an City's manufacturing industry has reached a crucial crossroads on its journey towards high-quality development. As the global economy gravitates towards digitalization, Tai'an's manufacturing sector faces both substantial opportunities and intense competition. To navigate this landscape, relevant government departments in Tai'an have been proactive. The Bureau of Industry and Information Technology rolled out the Digital Development Blueprint for Manufacturing. Meanwhile, the local government has allocated special funds to support manufacturers in adopting advanced digital technologies. The ultimate goal of these policies is to drive Tai'an's manufacturing industry to embrace digital transformation, improve production efficiency, and enhance its competitiveness in the global market, thus achieving high - quality, sustainable development. On April 23, 2023, the implementation plan "Tai'an City Manufacturing Industry Digital Transformation Implementation Plan(2023-2025)" was officially promulgated, outlining clear objectives: By 2025, Tai'an aims to achieve full coverage of digital and

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intelligent technological upgrading in all above-designated-size manufacturing enterprises, attain over 90% digital transformation rate among specialized, sophisticated, distinctive, and innovative ("little giant") enterprises, realize 75% full digitalization rate in key business processes of large-scale manufacturers, ensure that 53% of enterprises reach industrial-informatization integration enhancement (Industry 3.0) and innovation breakthrough (Industry 4.0) phases, strive to achieve an industrial-informatization development index of 125.These initiatives will significantly elevate the digital and intelligent manufacturing capabilities, driving profound transformations in manufacturing paradigms, production organization models, and industrial structures. To achieve these objectives, it is imperative to adhere to the logical framework of neo-quality productive forces, comprehensively cultivating digital productivity through three-dimensional cultivation encompassing labor force development, labor relations optimization, and production elements digitization [2].

Focusing on this strategic context, this study adopts the perspective of Tai'an manufacturing enterprises to investigate how digital productivity fuels new growth drivers for high-quality development in the manufacturing sector. Through an in-depth examination of its multi-dimensional driving effects and operational mechanisms, the research pursues dual objectives: providing intellectual support for establishing Tai'an as a provincial-level demonstration zone for manufacturing digital transformation, while offering theoretical foundations and practical guidance for related policy formulation.

2. Theoretical Hypotheses

As a new economic paradigm, digital productivity establishes digital infrastructure as its core foundational architecture, which encompasses core digital economic activities and efficiency-enhancing economic operations reliant on digital technologies, services, and data factors. This transformative force is propelling transformative advancements in manufacturing across product quality enhancement, ecological sustainability improvement, and economic efficiency optimization, thereby empowering high-quality development throughout the manufacturing sector [34].

First, technologies such as big data analysis, cloud computing, and AI-driven systems have played a crucial role in bringing about substantial development in digital productivity, enables manufacturing enterprises to precisely capture consumer demands, streamline production workflows, and elevate product quality standards. Through big data analytics, enterprises can gain real-time insights into consumer behavior patterns and preference dynamics. When integrated with intelligent equipment systems such as CNC machine tools and industrial robots, this capability enables flexible manufacturing configurations to fulfill customized demands, thereby enhancing product value-added attributes. By leveraging data integration and analytical processing, manufacturers optimize production techniques through three critical pathways: curbing resource waste along the value chain, boosting production efficiency indices, and ultimately elevating product quality benchmarks. The strategic deployment of CNC machining centers and industrial robotic systems not only ensures micrometer-level operational consistency but also significantly mitigates human error factors, establishing a robust quality assurance framework throughout manufacturing processes.

Second, the transformation of manufacturing towards green, low - carbon, and sustainable operations has been expedited by the progress of digital productivity [5]. By leveraging virtual simulation models and intelligent optimization technologies, enterprises can implement eco-friendly solutions across product design, material sourcing, and production processes, effectively reducing energy consumption and material waste. Big data systems enable real-time monitoring of resource utilization during production, allowing companies to optimize resource allocation and minimize inefficiencies. Furthermore, through big data analytics and IoT-enabled platforms, manufacturers can precisely track pollutant emissions, dynamically adjust production strategies, and significantly reduce harmful discharges, thereby driving the transition to environmentally sustainable manufacturing.

Third, digital technologies, when applied, have led to a notable enhancement of the economic efficiency in manufacturing. Through various control systems and data analysis tools, enterprises can real-time monitor material usage, inventory turnover, and other indicators, optimize production plans, and improve management efficiency. Technologies such as blockchain and the Internet of Things (IoT) have promoted data sharing and collaboration across supply chain links, resolving connection and interaction issues in traditional supply chains and enhancing supply chain transparency and efficiency. Through flexible division of labor regulation and integration of production and consumption, enterprises can achieve economies of scale and scope, reduce production costs, and enhance market competitiveness.

The development of digital productivity has not only driven improvements in product quality, ecological environment, and economic efficiency within the manufacturing industry but also accelerated the sector's transformation toward intelligent, green, and efficient models. The convergence of big data, cloud computing, the Internet of Things (IoT), and blockchain technologies is propelling manufacturing's transition from a traditional resource - reliant framework to a knowledge - driven, sustainable development model. This evolution bolsters the competitiveness of manufacturing enterprises and simultaneously furthers societal sustainable development [6]. Based on this, the following hypothesis is proposed:

H1: Enhancing digital productivity in Tai'an City will significantly promote the high-quality development of manufacturing enterprises.

3. Research Design

3.1 Variable Selection and Data Source

3.1.1Dependent variable

High-Quality Development Index of Manufacturing Enterprises in Tai'an City. Based on the connotation of high-quality manufacturing development and the theoretical analysis above, this study constructs an indicator system with three dimensions (Product Quality, Ecological Environment, Economic Performance) as shown in Table 1. The Mdh index is then calculated using the entropy method.

Table 1. Evaluation Indicator System for High-quality Development of Manufacturing Enterprises

First-Level Indicator	Second-Level Indicator	Indicator Description
Product Quality	R&D Intensity	Internal R&D Expenditure of Industrial Enterprises above Designated Size / Main Business Revenue (+)
	Patents per Capita	Invention Patent Applications of Industrial Enterprises above Designated Size / R&D Personnel (+)
	R&D Personnel Share	R&D Personnel of Industrial Enterprises above Designated Size / Total Employees (+)
	Product Quality Pass Rate	Qualified Product Quantity in Manufacturing / Total Product Quantity (+)
Ecological Environment	SO_2 Emission Intensity	ndustrial SO_2 Emissions / Industrial Added Value (-)
	Ammonia Nitrogen Emission Intensity	Industrial Ammonia Nitrogen Emissions / Industrial Added Value (-)
	Industrial Solid Waste Utilization Rate	Comprehensive Utilization of Industrial Solid Waste / Industrial Solid Waste Generation (+)
	Energy Consumption Intensity	Energy Consumption / Industrial Added Value (-)
Economic Performance	New Product Input-Output Ratio	New Product Sales Revenue of Industrial Enterprises above Designated Size / New Product Development Expenditure (+)
	Operating Profit Margin	Operating Profit of Manufacturing / Main Business Revenue of Manufacturing (+)
	Labor Productivity	Industrial Added Value / Number of Employees in Manufacturing (+)
	Average Wage	Total Wages of Urban Employees in Manufacturing / Number of Employees (+)

Note: Positive and negative signs in parentheses indicate indicator attributes (positive/negative direction)

3.1.2 Independent variable

Digital Productivity Index of Tai'an City. This study constructs a measurement indicator system for digital productivity from three dimensions digital technology, digital talent, and digital platforms—focusing on representative areas of the digital economy (see Table 2).

3.1.3 Control variables

The municipal-level control variables selected for this study include the urbanization rate,

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government support, and consumption level. The enterprise-level control variable set D mainly includes: firm age, firm size, profit margin, debt ratio, leverage ratio, and capital-output ratio.

Table 2. Indicator System for Digital Productivity of Tai'an City

First-level	Second-level	Third-level
Digital Technology	Digital Technology Products	Main Business Revenue of Manufacturing of Communication Equipment, Computers, and Other Electronic Equipment
		Import Volume of Manufacturing of Communication Equipment, Computers, and Other Electronic Equipment
		Export Volume of Manufacturing of Communication Equipment, Computers and Other Electronic Equipment
		Business Revenue of Software and Information Technology Services
	Digital Technology Foundation	Number of Digital Technology Patents of Enterprises
		Proportion of R&D Investment in Digital Technology of Enterprises
		Degree of Digitization of Enterprises
Digital Talent	Total Number of Digital Talent	Number of AI Professionals
		Number of Big Data Professionals
		Number of IoT and Industrial Internet Professionals
	Digital Talent Structure	Proportion of Talent with Higher Education
		Proportion of Female Digital Talent
		Proportion of Talent in Private Enterprises
		Proportion of Talent in Traditional Manufacturing
		Proportion of Talent in Emerging Manufacturing
Digital Platforms	Platform Economy	Proportion of Enterprises Active on International E-commerce Platforms
		Proportion of Enterprises Active on Domestic E-commerce Platforms
		Number of Self-built Websites Owned by Enterprises
		E-commerce Sales Revenue
	Platform Infrastructure	Proportion of New Product Sales Revenue to Main Business Revenue
		Expenditure on Enterprise Technological Transformation
		Expenditure on Enterprise Technology Introduction

3.2 Model Construction

Based on the theoretical analysis above, to test Hypothesis 1, this study constructs the following baseline regression model using panel data. Hausman test results significantly indicate that the fixed effects model (FE) is superior to the random effects model (RE). Considering the potential individual and time trend effects of digital economy and high-quality manufacturing development across enterprises and years, and to reduce the impact of unobservable factors, this study employs a two-way fixed effects model (individual and time) for empirical testing.

$$Mdh_{it} = \alpha_1 + \alpha_2 De_{it} + \sum_{j=1}^{9} \alpha_{jt} D_{jt} + \sigma_{it} + \mu_{it} + \varepsilon_{it} \quad (1)$$

In the model, i represents individual enterprises, t represents the year. The dependent variable is the High-quality Development Index of manufacturing enterprises, and the independent variable is the Digital Productivity Index. D denotes the set of control variables, where α j (j=1, 2, 3, …, 9) are the impact coefficients of the urbanization rate, government support, consumption level, firm age, firm size, profit margin, debt ratio, leverage ratio, and capital-output ratio on the high-quality development of the manufacturing industry. σ represents the individual fixed effects of enterprises, μ reflects the time-fixed effects of the year, and ε refers to the random disturbance term.

4. Empirical Results Analysis

4.1 Direct Effect Test of Digital Productivity Enabling High-quality Development of Manufacturing Enterprises

To compare the regression results and preliminarily examine the rationality of the model design, this study conducts econometric tests using three methods: Random Effects Regression (RE), Fixed Effects Regression (FE) without control variables, and Fixed Effects Regression (FE) with control variables. As shown in Table 3, regardless of the regression method and model applied, all regression coefficients associated with digital productivity are positive in value, and they meet the requirements of the significance test. Evidently, as the digital economy and

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manufacturing converge, digital productivity serves as a catalyst for high-quality growth among Tai'an's manufacturing enterprises. It effectively enhances resource allocation, streamlines R&D processes, and improves management within the manufacturing sector, thereby fueling overall development.

Incorporating control variables, as well as fixed effects for region, industry, and year, maximizes the fitness of the model. This indicates that the design of the baseline regression model is well - founded. Further application of the Hausman test strictly rejects the null hypothesis, leading this study to select the two-way fixed effects model for baseline regression. The results are presented in Column (3) of Table 3.

Table 3. Baseline Regression Results

	RE	FE	
De	0.2457*** (0.0646)	0.3562*** (0.0865)	0.3792*** (0.0836)
Ul			0.3700** (0.6116)
Gov			-0.2467** (0.1038)
Cs			0.1356*** (0.0459)
Age			0.3700** (0.6116)
Lnscale			-0.2063*** (0.0740))
Profitrate			0.1671*** (0.0322)
Debtrade			-0.4898*** (0.1414)
Levrate			0.1356*** (0.0459)
Kyrate			0.7479*** (0.2255)
Individual Fixed Effects	No	Yes	Yes
Year Fixed Effects	No	Yes	Yes
N	1705	1705	1705
R2	0.016	0.169	0.485

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. p-values are reported in parentheses.

In Column (3), after incorporating all control variables, the estimated coefficient of the digital economy stands at 0.3792, and it is significant at the 1% level. This finding suggests that as the digital economy and manufacturing industry are integrating deeply, digital productivity serves as new driving force for high-quality manufacturing development [78]. It effectively enhances resource allocation, R&D, and management efficiency within the manufacturing industry, thereby validating the theoretical hypothesis.

4.2 Endogeneity Treatment

Considering the potential reverse causality between digital productivity and high-quality enterprise development, the possibility that unobservable variables may simultaneously affect their relationship, the core independent variable digital productivity may suffer from endogeneity issues. To address this, this study conducts a Hausman test for endogeneity. The results strongly reject the null hypothesis, this verifies that endogeneity exists in the model. Therefore, it is necessary to improve the baseline model through endogeneity treatment. The regression results after endogeneity treatment are presented in Table 4.

Table 4. Addressing Endogeneity Issues

	IV (1)		IV (2)	
	First Stage	Second Stage	First Stage	Second Stage
INO_ fm	0.002*** (6.01)			
INO_ xx	0.001*** (7.60)			
INO_ wg	0.002*** (2.81)			
De-1			0.170*** (8.32)	
De -2			1.009*** (9.10)	
De		0.128*** [4.06]		0.818*** [6.15]
Cragg-Donald Wald F Statistic	12.401	30.431	28.507	14.004
Hansen J, P-value	0.575		0.981	
control variable	Yes	Yes	Yes	Yes
N	1203		1372	

Note: Parentheses ( ) report t-values, and square brackets [ ] report z-values.

Table 4 reports the two-stage results of the 2SLS regression using two instrumental variables (IV). Columns (1)-(2) employ the number of invention patent applications (INO_ fm), utility model applications (INO_ xx), and design patent applications (INO_ wg) as instrumental variables. The first-stage F-statistic of 12.401, exceeding the threshold of 10, indicates the absence of weak

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instrument problems. Meanwhile, the Hansen J statistic yields a p-value of 0.575, we accept the null hypothesis that the instruments are uncorrelated with the error term. This acceptance serves to verify the exogeneity of the instruments. These results confirm that the selected instrumental variables - INO_ fm, INO_ xx, and INO_ wg - satisfy both the relevance and exogeneity requirements, thus justifying their validity. Turning to the estimation results, the coefficient value of 0.128 is obtained for our primary explanatory variable. Statistical tests show this coefficient to be significant at the 1% significance level. This estimate maintains the same sign as the baseline regression coefficient of 0.3792, though with a reduced magnitude. This suggests that while some degree of endogeneity exists in the model variables, it does not fundamentally alter the substantive conclusions drawn from the baseline analysis.

5. Policy Recommendations

5.1 Strengthen Top-Level Design and Institutional Safeguards

Deepen the implementation of the Tai'an City Three-Year Action Plan for Digital Economy Development (2023-2025), with a focus on advancing the "Ten Major Digital Industrialization Projects" and "Eight Key Industrial Digitization Initiatives." Establish a cross-departmental coordination mechanism to ensure dynamic alignment between policies and market demands. Drawing on the experience of the "Yellow River Basin Digital Economy Competence Center," set up a municipal-level Digital Economy Coordination Office to integrate resources from departments such as Development and Reform, Industry and Information Technology, and Finance, thereby addressing policy fragmentation [9].

5.2 Accelerate the Digital Transformation of Industries

Targeting traditional industries (e. gtextiles, equipment manufacturing), promote the application of Daiyin Group's "Cross-border Apparel Supply Chain Cloud Management Platform" to share best practices. Introduce "competitive subsidy programs" for digital transformation to reduce technology upgrade costs for enterprises. Establish a "Digital Diagnostic Service Provider Pool", certifying over 30 qualified providers to deliver tailored smart transformation solutions for SMEs, with a focus on production process optimization and energy consumption monitoring. Cultivate new growth engines in semiconductors and advanced computing [10]. Accelerate key projects such as Guoxing Aerospace's Tai'an Satellite Internet Industrial Base and Hongjinsheng Electronics Industrial Park, aiming to build 3-5 digital industry clusters each exceeding RMB 10 billion in output by 2025.Support Taishan District in developing an "Aerospace Information Industrial Park" focusing on satellite internet and BeiDou Navigation technologies. Establish a RMB 1 billion industrial guidance fund to enable cutting-edge R&D and commercialization.

5.3 Strengthen the Innovation Ecosystem and Talent Development Infrastructure

Promote the "Taishan Craftsman Academy" model by partnering with Shandong Agricultural University, Inspur Software, and other institutions to launch specialized training programs in artificial intelligence and industrial Internet. The initiative aims to cultivate over 5,000 interdisciplinary digital talents by 2025.Establish a "Digital Economy Innovation Consortium" to facilitate joint laboratories between enterprises (e.g., Euroka Mining Technology, Zhongzhi Electronics) and universities, focusing on R&D breakthroughs in "bottleneck technologies" such as smart sensors and industrial software.

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