Intelligent Manufacturing, Industrial Structure, and Competitive Advantage: An Analysis Based on the Resource-Based View

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ABSTRACT

Smart manufacturing combines the technologies of artificial intelligence and the manufacturing industry, which stimulates the modernization and synchronization of both internal and external resources and, therefore, transforms the competitive advantages of the firms. Nevertheless, the existing literature in this area has not been able to clarify the interactions between the current resource endowment of firms and intelligent manufacturing innovations in the creation of competitive advantage, as well as it has not been able to determine the conditions of the boundaries of effects. Basing on the resource-based view (RBV) theory, the given study centers on the issue of the improvement of the competitive advantage of the firms through intelligent manufacturing in terms of substitutability and complementarity of the resources and the role of the industrial structure as the mediator. Based on empirical evidence of the A-share listed manufacturing firms in China (2011 2022), the present study shows that intelligent manufacturing contributes remarkably to the competitive advantage of the enterprises, which is increased by the greater extent of industrial structure supererogation and rationalisation. According to mechanism tests, intelligent manufacturing increases competitive advantages primarily through the source of enterprise production efficiency and information efficiency. Tests of heterogeneity indicate that the role of intelligent manufacturing on competitive advantage is heterogeneous to varying degrees of regional digitalisation and enterprise cost pressure. The main value of this research would be that it extended the theoretical view of related studies to understand the inherent transmission process of the concept of intelligent manufacturing-resource substitution and complementarity-competitive advantage. Moreover, this study, through the introduction of various contextual variables, i.e., industrial structure, regional digitalisation rates, and the cost pressure faced by firms, systematically considers the boundary conditions under which intelligent manufacturing influences firm competitive advantage. The work expands the application of the RBV theory in the area of intelligent manufacturing and offers information to companies that pursue the strategy of intelligent manufacturing and local government that optimises industrial conditions.

Keywords: Intelligent manufacturing, Competitive advantage, Industrial structure supererogation, Industrial structure rationalisation, Text analysis method

1. Introduction

In the period of 2012-2024, the contribution made by the manufacturing industry of China went up to 40.5 trillion yuan, with a market share of close to 30 percent in the whole world, and it has consolidated its leadership position. Nevertheless, with the ongoing increase in the scale of industries, the growth rate of the manufacturing sector of China has been slowing down with increasing pressure both domestically and internationally. The quest of high-quality improvement in the manufacturing industry is currently faced by challenges that have never been seen before [1]. To this, the State Council of the People's Republic of China published the Made in China 2025 report, which highlighted the need to continue developing the integration of information technology and industrialisation, as well as the structural reiteration of the manufacturing sector, in order to meet the strategic goal of becoming a powerful manufacturing giant.

At present, the manufacturing industry is being radically reconfigured by a transformative wave of information technology that can be seen through big data, cloud computing and artificial intelligence [2,3,4]. As a powerful and prospective technology, Artificial Intelligence (AI) can increase the performance and competitiveness of organisations in certain situational conditions. In an example of AI-supported industrial robots, the automation of production processes, optimisation, and quality enhancement of products are observed in manufacturing businesses [5]. Digital twins' technology would help businesses to optimise decision-making, minimise the time of disruption, and minimise costs by analysing data in real-time and predicting models [6]. The adoption of blockchain technology within the supply chain management of manufacturing, traceability, and compliance enhances efficiency in its operations, security, and transparency [7]. In addition, since ChatGPT is an example of AI technology of the new generation, the application of intelligent manufacturing systems to solve different situation tasks and enhance productivity through dataset pre-training, fine-tuning in a specific situation, and the reinforcement learning of domain knowledge [8], [9] may be called a revolution in the manufacturing industry. The natural process of adopting artificial intelligence technology in the manufacturing industry does not only increase the essential internal value chain variables like product design, production, operations, sales, management, and services, but also the core interests of the entire industry chain. This convergence opens up new possibilities of solving the bottlenecks in the development of the sector. Moreover, the flow, the coordination and evolution of factors of production depend on variations of industrial structural characteristics [10], [11]. The differences, in their turn, influence the factor of production and support of infrastructure that can be secured by intelligent production, usage of resources and synergy between industries that can be achieved. As a result, the structure of the industrial organization is one of the most important external environmental factors that determine the capacity of manufacturing companies to achieve competitive advantages via smart transformation [12], [13].

The role of intelligent manufacturing in businesses has received a lot of scholarly concern in recent years. The primary focus of the existing studies is the influence of intelligent manufacturing on the performance of firms [14], [15], operational efficiency [16], [17], cost [18], innovation [19,20,21] and total factor productivity [22] and the development of green [23], [24], and personnel structure [25] in the enterprises. Out of the comparatively small number of studies examining the connection between intelligence and competitive advantage, Kemp (2023) argues that situated AI generates competitive advantage in firms by situated, bounding, and recasting organisational activities, which constitutes a holistic theoretical and analytical framework of the interaction between AI and the competitive advantage of firms [26]. In the same way, Sun et al. (2022) study the mechanisms that are inherent in small and medium enterprises that help them to retain a competitive advantage by using AI innovation ecosystems [27]. Nevertheless, the academic literature has not adequately disclosed the interaction between the current resource endowments of the firm and smart manufacturing technological advances when it comes to unleashing some synergies that belie competitive advantages. Based on the RBV view of resource complementary and substitutable, this paper examines the role of intelligent manufacturing in increasing competitive advantage through efficient utilisation of resources held by a firm, which broadens the conceptual framework of intelligent manufacturing. Moreover, the literature has not adequately given theoretical explanations and empirical experiments on how intelligent manufacturing determines the market competitive advantage of a firm. This paper finds the two-way through which intelligent manufacturing enhances efficiency of corporate production and information allocation optimisation. It thus fills gaps in the literature that currently exists as well as addressing and building on the seminalion of Teece [28] that technological innovation affects performance within the market by augmenting complementary assets and organisational capabilities of a firm. Lastly, the previous studies have also been less concerned with the heterogeneous impact of intelligent manufacturing in such complex external industrial frameworks and market conditions. To overcome this gap, the research uses the feature of industrial structure to further discuss the boundary conditions of the role of intelligent manufacturing on the competitive advantages of a firm on the product market.

In that respect, the given research problem is the following: how does intelligent manufacturing provide enterprises with a competitive advantage based on RBV theory, and how does the in-depth heterogeneity of the industrial structure influence the given process. The main contributions of this study are realized in various aspects. First, according to the resource-based perspective, we examine the inherent process of intelligent manufacturing on the competitive advantage through the lens of substitution and complementarity of the resources of the research, which expands the theoretical perspectives of related studies. Second, we examine how intelligent manufacturing affects the competitive edge of companies and deepen the literature on the research of the economic implications of intelligentisation of companies. Third, we look at the impacts of the industrial structure conditions on the acquisition of competitive advantages by manufacturing enterprises through intelligentisation, hence, enriching the contextual understanding of the impacts of intelligent manufacturing. The paper is presented in the following way. The second part reviews the literature on related works and includes a theoretical analysis, and the research hypotheses. The data sources, definition of the variables and model design are described in the section of sample and methodology. The section of empirical results can be considered as the representation of the outcomes of baseline regression, endogenous treatment, robustness tests, mechanism tests, and heterogeneity analysis. The conclusions and implications section are a summary of the conclusions, the implications, and suggestions of directions that research can take in the future.

2. Literature Review and Research Hypotheses

2.1 Intelligent Manufacturing and Competitive Advantage

The Resource-Based View (RBV) offers an invaluable theoretical model in the explanation of the complex relationship among resources and competitive advantage [29], [30]. Following RBV theory, it is possible to analyze the impacts of artificial intelligence application to manufacturing companies on their competitive edge based on the two aspects of resource substitution and resource complementarity. Being a paradigm of new production, intelligent manufacturing changes the substitution and complement of resources, affecting production and information efficiency of manufacturing companies [31,32,33]. The result of these changes, in its turn, also influences the competitive advantage of the enterprises. Based on this, this section examines how the development of intelligent manufacturing impacts on production and information efficiency in terms of resource substitution and complementary, and thus increase the competitive advantage of firms.

2.1.1 Productivity channel based on resource substitution and complementarity

In terms of resource substitution, the intelligence development of manufacturing firms takes the form of substituting low-end labour with machines [34]. Intelligent machines can also be continuously operated 24 hours per day with minimal error which makes them higher productivity compared to the traditional low-end labour [35], [36]. In addition, AI systems have large information gathering and processing capabilities, which hugely improve the richness and accuracy of forecast data. Therefore, AI-based predictions are more reliable and scientifically supported sources of decision making than traditional human predictions [37]. Thus, the level of artificial intelligence forecasting substitution of the information forecasting (performed by human beings) is certain [38]. This replaceability, especially in predictive information, increases the market foresight of an enterprise, which is able to adapt production arrangements to the alterations of the product demand. In addition to the increase in production efficiency, the replacement of AI resources also enhances the competitive advantage of an enterprise in a product market.

Another point that is made by RBV is the contribution of resource complementarity to a competitive advantage based on unique combination of resources [39]. The AI development in manufacturing businesses promotes the complementary interactions between workers and machines resulting in the large-scale situational production. This synergy contributes to flexibility and productivity of production enabling enterprises to react quickly to changes in the market [40], [41]. This kind of flexibility is more capable of meeting the demands of customers in differentiated products and thus enhancing competitiveness in the product market [42]. Moreover, the optimisation of resource allocation, driven by AI, creates an insufficient sum of complementary benefits in operational processes and product development, which enhances production efficiency and value creation in enterprises.

2.1.2 Information efficiency channel based on resource substitution and complementarity

Considering the resource substitution perspective, the introduction of intelligent information resources substitutes the traditional information resources in the manufacturing enterprises. The disadvantage is that traditional firms are often characterised by a high level of information asymmetry, inefficiency in the transfer of information, and internal information islands within the procurement, production, sales and management departments [43]. Smart manufacturing involves the combination of smart technologies and machines to revolutionize the process of information transmission. This replacement makes it possible to connect internal processes in real time, which allows the sharing of information in a collaborative manner, eliminating asymmetry, and transfering the data in a more effective way [44]. Enhanced flow of internal information assists business enterprises to surmount the phenomenon of information islands, lower production and operation expenses, and strengthen the competitive ability [45]. Also, replacing intelligent information resources with traditional ones enhances the quality of information disclosure [46], [47], enhancing the accessibility of information on products customers, minimizing information asymmetry between supply and demand and ultimately, increasing competitors' advantage. The perspective of resource complementarity states that the intelligent information resource development can help to integrate the external and internal resources by collaborating with the external stakeholders. The traditional manufacturing firms have a tendency of having difficulties accessing timely and correct market information or tend to be expensive to acquire. Developments in intelligent information resources improve the capabilities of firms to gather, handle, and manipulate the external data. These systems can be used to bridge the information-physical systems gaps to enhance collaborative information sharing along the industrial value chain by utilizing intelligent technologies [48]. Enterprises and stakeholders can complement resources and make joint decisions based on common information, which minimises asymmetry and transaction costs as well as enhances the use of information. Such a partnership will enable the businesses to gain better market information and resource base, which will enhance competitiveness. Simply put, the intelligent information resources development becomes an impetus to enhanced information sharing and collaboration, thus enhancing enterprise competitiveness.

To sum up the intelligent manufacturing development enables substitution and complementing of intelligent resources to traditional ones. This will improve production and information efficiency, thus competitive advantage of firms. On this analysis, Hypothesis 1 is put forward.

Hypothesis 1. Intelligent manufacturing enhances the competitive advantage of enterprises.

2.2 Intelligent Manufacturing, Industrial Structure and Competitive Advantage

The industrial structure is another key external environmental factor that affects the generation of competitive advantages by the enterprises using smart manufacturing. Due to the differences in the industrial structure, there are variations in the evolution and coordination of the factors of production. To some degree, these differences influence the infrastructure support in the regions and the influence of the so-called peer group effect that is offered to enterprises that carry out intelligent manufacturing [49], [50]. This segment discusses the issue of the impact of industrial structure on the connection of intelligent manufacturing and competitive advantage, with special reference to industrial structure supererogation and industrial structure rationalisation.

2.2.1 Intelligent manufacturing, industrial structure supererogation and competitive advantage

Industrial structure supererogation is the process of gradual development of big industries in a territory, when the emphasis on manual labour is gradually replaced by the capital investment and technological breakthroughs. Such transformation includes the shifts in the relative importance of different industrial branches and the increase in the productivity of the factors [51]. The effects of industrial structure supererogation on the relationship between intelligent manufacturing and competitive edge can be examined in three aspects, which are supporting the factors of production, improving infrastructure, and the presentation of the peer group effect. To begin with, there is the fact that the higher the level of industrial structure supererogation, the higher the percentage of advanced production inputs and skilled labour. Because smart production requires such sophisticated aspects, the industrial structure upgrading provides the manufacturing business in the locality with a rich supply of high-level resources, which facilitates their attainment of competitive power in product markets. Second, in connection with infrastructure, with the speed of industrial upgrading, industries are in need of more advanced supporting infrastructure. In countermeasures, local governments invest in better facilities, and as a consequence, this contributes to intelligent manufacturing development. Therefore, there is supererogation of industrial structure infrastructural support that accumulates competitive advantages of smart manufacturing. Third, taking into account the so-called peer group effect, intelligent manufacturing businesses, obsessed with the need for sophisticated factors and infrastructure, are inclined to concentrate in highly industrialised areas. The ensuing concentration leads to positive interaction between firms [52], which also leads to the increment of intelligence levels as a unit and adds competitive advantages. Considering the above study, Hypothesis 2 is put forward.

Hypothesis 2. The greater the degree of industrial structure supererogation, the greater the promotion impact of intelligent manufacturing on the competitive advantage of enterprises.

2.2.2 Intelligent Manufacturing, industrial structure rationalisation and competitive advantage

The concept of industrial structure rationalisation touches on how the factors of production are distributed, coordinated and flowed in various industries. It stresses the need to show proportional balance, correlation as well as alignment between the different industries, which are indications of resource efficiency allocation. This metric measures how much the factor inputs are coupled with the output structures [49]. The impacts of rationale of the industrial structure in terms of the relationship between competitive advantage and intelligent manufacturing can be broken down into three aspects: factor mobility, inter-industry coordination, and resource utilisation efficiency. To begin with, an industrial structure that is more rationalised improves free movement of the factors of production across industries. This helps manufacturing enterprises to interoperate with its upstream and downstream partners using intelligent technologies and encourages the sharing of the key resources including technology, capital, and information. These exchanges can be used to fill resource gaps, enhance resource advantages and eventually more competitive positions of firms. Second, the increased degree of inter-industry coordination will help manufacturing enterprises to communicate with stakeholders in the value chain in an effective way. This coordination increases resource complementarity and joint decision-making through smart ways and it gives firms the external assistance they need to enhance their competitiveness. Last, a high-resource utilisation, which is a hall mark of a highly rationalised industrial structure, promotes easy flow, coordination, and integration of information resources among the interdependent firms. Through the facilitation of smart manufacturing, this efficiency minimizes the information asymmetry and transaction costs and improves cooperation and competitive positioning. Based on this, Hypothesis 3 is developed.

Hypothesis 3. The larger the degree of rationalisation of industrial structure, the greater the effect of promotion of intelligent manufacturing on the competitive advantage of the enterprises.

3. Research Design

3.1 Sample and Data Collection

The sample of the research includes the A-share manufacturing firms listed on Shanghai and Shenzhen stock exchanges in China from 2011 to 2022 (publicly). The sampling procedure is done in the following manner: (1) the samples of ST, *ST and PT firms in special states are excluded; (2) samples with missing values in variables used in the basic regressions are excluded; (3) all continuous variables are treated with a 1% winsorization on the sample to alleviate the impact of outliers. The last unbalanced panel data consists of 14,709 sample observations. The data concerning industrial structure are mainly obtained on the official websites of the National Bureau of Statistics of China and provincial statistical bureaus, and the data concerning financial and governance are mainly obtained on the CSMAR database, the CCER database, and CNRDS database. cninfo.com.cn provides annual reports of listed companies.

3.2 Variable Measurement

3.2.1 Competitive advantage

The existence of a competitive edge in an enterprise implies that an enterprise has greater competitive power and better competitive position in the industry. On the basis of the previous studies, we indicate the competitive advantage of a business on the basis of competitive strength and competitive position. Concerning power in competition, scholars determine the power of firms in the market based on building the Lerner Index [53], [54]. This index is determined as a ratio between operating profit and sales and it is used to measure the degree of pricing power whereby, the higher the Lerner Index, the higher the competitive power. In terms of competitive position, a higher excess main business profit margin, will translate to a superior competitive position in the industry, which is an indication of a greater competitive advantage in the product market [55]. We, therefore, use the Lerner Index to gauge the intensity of competitiveness of enterprises and use the excess ROA to advantage the competitive position of enterprises.

3.2.2 Intelligent manufacturing

We will use the text analysis technique, and our key word will be the frequency of words of artificial intelligence to develop the measure of intelligent manufacturing [56], [57]. The particular metrics are as follows: It should be based on Made in China 2025, Intelligent Manufacturing Development Plan (2016-2020), and recent Government Work Reports, further developing the feature words library connected with the AI technology, machine learning, intelligent analysis of data, and so on. And finally, a total of fifteen feature words that depict the dimensions of artificial intelligence technology such as artificial intelligence, business intelligence, image understanding, etc., are gathered. This is followed by search, matching, and counting of the word frequency of these feature words in these parts of annual reports of the firms that are labeled as management discussion and analysis (MD&A). It is through this that the word frequency is created about the direction of artificial intelligence technology. Based on the skewed nature of the data to the right, there is logarithmisation of the data to get the final proxy index of intelligent manufacturing.

3.2.3 Industrial structure

The industrial structure can broadly be categorized into two factors namely industrial structure supererogation and industrial structure rationalisation [51]. The most common of them is industrial structure supererogation that is gauged by the product of the share of output of the three major industrial sectors and labour productivity**.** The precise method of calculation is as follows:

$$ISS_{it} = \sum_{i=1}^{n} \left(\frac{Y_{it}}{Y_t}\right)\left(\frac{LP_{it}}{LP_{if}}\right) \quad [1]$$

where ISS_{it} represents industrial structure supererogation, $n = 3$, representing the three major industries, Y_{it} denotes the value of output of industry i, Y_t denotes the total output value of the three industries, LP_{it} represents the labour productivity of industry i, and LP_{if} denotes the labour productivity of industry i after the completion of industrialisation.

The industrial structure deviation index is used to measure industrial structure rationalisation, which is calculated as follows:

$$E = \sum_{i=1}^{n} \left|\frac{\frac{Y_i}{L_i}}{\frac{Y}{L}} - 1\right|, i \in \{1,2,3\} \quad [2]$$

where Y represents GDP, L represents total employment, i signifies a specific industry, and n denotes the total number of industries. When E approaches 0, it indicates a more rational industrial structure. Conversely, any positive deviation from 0 suggests an irrational industrial structure, with a greater positive score denoting an increased level of industrial structural irrationality.

3.2.4 Control variables

Building upon previous studies related to market competitive advantage, we select firm size (Size), the nature of equity (SOE), firm age (Age), financial leverage (Debt), corporate growth (Growth), corporate performance (ROA), proportion of R&D expenditures (R&D), proportion of fixed assets (Fix), cash flow (Currency), percentage of the largest shareholder's shares (CR1), firm Investment value (TobinQ), and industry concentration (HHI). Table 1 contains a full definition of each variable.

Table 1. Variable definitions

Variable type	**Variable name**	**Variable symbol**	**Definitions**
Explanatory Variable	Competitive strength	PCM	Lerner Index = (Sales Revenue - Cost of Sales - Administrative Expenses - Selling Expenses) / Sales Revenue
	Competitive position	ExROA	Excess Return on Total Assets = Corporate ROA - Industry Average ROA
Explanatory Variable	Intelligent manufacturing	Intelligence	Natural logarithm of intelligent word frequency + 1
Moderator	Industrial structure	ISS	Multiplication of output share and labour

Variable	supererogation		productivity by industry
	Industrial structure rationalisation	E	Industrial structure deviation index
Control Variable	Firm size	Size	Natural logarithm of total assets
	Nature of equity	SOE	1 for state-owned enterprises, 0 otherwise
	Firm age	Age	Current year - year of incorporation +1
	Financial leverage	Debt	Total liabilities/total assets
	Corporate Growth	Growth	Revenue growth rate
	Corporate performance	ROA	Net profit/total assets
	Proportion of R&D expenditures	R&D	R&D expenditure/total assets
	Proportion of fixed assets	Fix	Fixed assets/total assets
	Cash flow	Currency	Monetary funds/total assets
	Proportion of shares held by the largest shareholder	CR1	Number of shares held by the largest shareholder/total number of ordinary shares outstanding
	Firm Investment value	TobinQ	Market value / (total assets - net intangible assets - net goodwill)
	Industry concentration	HHI	Herfindahl-Hirschman Index of operating revenues of the top 5 companies in the industry

Source: By authors.

3.3 Model

To examine the influence of intelligent manufacturing on the competitive advantage of businesses and to assess the moderating impact of industrial structure, we established the subsequent model.

$$PCM_{i,t}(ExEOA_{i,t}) = \alpha_0 + \alpha_1 Intelligence_{i,t} + \alpha_2 Controls_{i,t} + \mu_i + \theta_t + \xi_j + \vartheta_p + \varepsilon_{i,t} \ldots [3]$$

$$PCM_{i,t}\left(ExEOA_{i,t}\right) = \beta_0 + \beta_1 Intelligence_{i,t} + \beta_2 ISS_{i,t} + \beta_3 Intelligence_{i,t} \times ISS_{i,t} + \beta_4 Controls_{i,t} + \mu_i + \theta_t + \xi_j + \vartheta_p + \varepsilon_{i,t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [4]$$

$$PCM_{i,t}\left(ExEOA_{i,t}\right) = \gamma_0 + \gamma_1 Intelligence_{i,t} + \gamma_2 E_{i,t} + \gamma_3 Intelligence_{i,t} \times E_{i,t} + \gamma_4 Controls_{i,t} + \mu_i + \theta_t + \xi_j + \vartheta_p + \varepsilon_{i,t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [5]$$

where i and t represent firm and year, respectively. PCM represents competitive strength, $ExROA$ represents competitive position, $Intelligence$ represents intelligent manufacturing, $Intelligence \times ISS$ represents the interaction term of intelligent manufacturing and industrial structure supererogation, and$Intelligence \times E$ represents the interaction term of intelligent manufacturing and industrial structure deviation index, and $Controls$ is the group of control variables. To mitigate the effect of heteroskedasticity, robust standard error-adjusted t-statistics are used in all regression equations. In addition, we also simultaneously control for individual (μ_i), year (θ_t), industry (ξ_j) and region (ϑ_p) fixed effects.

4. Empirical Results

4.1 Descriptive Statistics

Table 2 displays the descriptive statistics of the primary variables. The findings indicate that the mean of PCM and ExROA are 0.1118 and -0.0021 respectively, and the standard deviations of the mean of the sample firms are 0.1082 and 0.0594 respectively which means that there is a big difference in both the competitive strength and the competitive position of the sample firms. The lowest score of Intelligent Manufacturing (Intelligence) is 0 which implies that there are companies whose Intelligent manufacturing is not mentioned at all in the MD &A section of their annual reports. Also, the mean of the Industrial Structure Supererogation (ISS) and Industrial Structure Rationalisation (E) are 1.9428 and 1.2268, respectively, and their standard deviations are 0.7985 and 0.5323, respectively, which show that there is a large difference in the status of industrial structure in each province.

Table 2. Descriptive statistics of variables

Variable	Obs.	Mean	SD	Min.	Max.
PCM	14,709	0.1118	0.1082	-0.2698	0.4650
ExROA	14,709	-0.0021	0.0594	-0.2198	0.1732
Intelligence	14,709	0.2572	0.5712	0.0000	2.7081
ISS	14,709	1.9428	0.7985	0.6811	4.6717
E	14,709	1.2268	0.5323	0.5439	3.2525
Size	14,709	22.3087	1.1742	20.0259	25.7653
Age	14,709	2.9846	0.2826	2.1972	3.6376
SOE	14,709	0.3463	0.4758	0.0000	1.0000
Debt	14,709	0.4162	0.1867	0.0621	0.8754
Growth	14,709	0.1417	0.3068	-0.4664	1.7504
ROA	14,709	0.0439	0.0620	-0.1825	0.2321
RD	14,709	0.0230	0.0163	0.0003	0.0859
Fix	14,709	0.2371	0.1329	0.0196	0.6265
Currency	14,709	0.1705	0.1104	0.0192	0.5869
CR1	14,709	0.3457	0.1422	0.0903	0.7430
TobinQ	14,709	2.1736	1.3570	0.8955	8.9715
HHI	14,709	0.0895	0.0710	0.0181	1.0000

Source: By authors.

4.2 Baseline regression

Table 3 indicates the regression analysis of the effect of intelligent manufacturing on the competitive advantage of businesses in Columns (1) and (2). Under (1) column, which dwells upon the competitive strength of enterprises (PCM), The Intelligent manufacturing (Intel) has 0.0035 regression coefficient, which is significant at 1% level. On the same note, Column (2) displays the results of regression in terms of the outcome of intelligent manufacturing on the competitive position of enterprises (ExROA), intelligent manufacturing (Intelligence) is the regression coefficient, and its value is 0.0016 and is statistically significant at the 1% level. These results show that smart manufacturing improves the competitive advantage of manufacturing organizations to a considerable extent, which supports Hypothesis 1. Passing to the columns (3)-(4), the outcomes demonstrate the regression findings of the moderating effect of industrial structure supererogation. The coefficients of interaction terms intelligent manufacturing and supererogation of industrial structure (IntelligencexISS) are all considerably positive. This means that the greater locality of the business in terms of the extent of industrial structure supererogation enhances the positive effects of intelligent manufacturing on the business competitive advantage, which confirms Hypothesis 2. The regression output of the moderating effect of the industrial structure rationalisation is contained in columns (5)-(6). The coefficients of the interaction term of intelligent manufacturing and industrial structure deviation index (IntelligencexE) are all negative significantly. It is important to note that the level of deviation of the industrial structure index (E) is an inverse measure, whereby the higher the value, the more irrational the industrial structure. Thus, the findings in column (5)-(6) indicate that increasing rationalisation of the industrial structure in the locality of the business (indicating more balanced industrial structure) enhances the positive influence of intelligent manufacturing on the competitive advantage of business. This supports Hypothesis 3.

Table 3. Basic regression results

	(1)	(2)	(3)	(4)	(5)	(6)
	PCM	ExROA	PCM	ExROA	PCM	ExROA
Intelligence	0.0035*** (3.1615)	0.0016*** (5.8585)	-0.0106*** (-3.5654)	0.0003 (0.4399)	0.0156*** (5.4713)	0.0036*** (4.8055)
Intelligence×ISS			0.0062*** (4.9934)	0.0006** (1.9671)		
Intelligence×E					-0.0118*** (-4.6516)	-0.0020*** (-2.8644)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.509	0.505	0.510	0.505	0.509	0.505
Observations	14709	14709	14709	14709	14709	14709

Note: Robust t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, and* $p < 0.1$.

Source: By authors.

4.3 Endogenous Treatment

4.3.1 Instrumental variable (IV) approach

The findings of the benchmark regressions indicate that intelligent manufacturing increases the benefit of the listed manufacturing companies. Despite the consideration of individual effects, year effects, industry effects, and regional effects to partially resolve the endogeneity, there is still a possibility of the reverse effects meaning that companies that have better competitive advantages would adopt smarter manufacturing strategies. In a bid to take care of such a situation, an instrumental variable method is used. The number of AI enterprises (IV1) and its level of digitisation (IV2) is the chosen instrumental variable in the location of the enterprises, the provinces. The least squares method applied is two-stage. The digitisation degree of a particular province is measured by the natural logarithm of the frequency of the word "digitisation" in the Baidu index of that specific province. There are two reasons why instrumental variables were chosen; First, there is a peer group effect on digitisation and intelligence level among enterprises based in the identical location [58]. In case the amount of AI businesses in a province is bigger and the overall level of digitisation is greater, it may be actively involved in raising the level of intelligence displayed by local manufacturing companies. Therefore, the data on AI businesses and digitisation rate of the host province have a positive relationship with the degree of intelligent manufacturing of business. Second, on exclusivity, these provincial in level indicators do not have a direct impact on the competitive advantage of a firm. The columns of Table 4 (1)-(3) show the results of the two-stage instrumental variables regression. The results of the Cragg-Donald Wald F-test and Hansen J-test indicate that there are no weak identification and over-identification issues. Namely, the findings in column (1) indicate that the number of AI firms and the level of digitisation in the host province have a strong and positive relationship with intelligent manufacturing of firms. The findings in column (2) and (3) are that with the endogeneity issue factored in, intelligent manufacturing still greatly increases the competitive advantage of the firms, which is in line with the baseline regression findings.

4.3.2 Propensity score matching (PSM) method

To address the impact of the possible bias during the sample selection, we use the propensity matching score model (PSM) to match the base sample. In the light of the presence of similar control groups, radius matching is used to enhance matching efficiency. The matching turns out to be effective as the experimental and the control groups pass the common support test and balance test. Table 4 columns (4)-(5) indicate the results of the regression when it has been matched, and it indicates that regression coefficients of intelligent manufacturing (Intelligence) are significantly positive. This is an indicator that smart manufacturing can contribute greatly to the competitive advantage of companies, which is the same as the benchmark regression outcomes. Besides, kernel matching is also used with the results that are aligned with the benchmark regression results. In short, even in cases that sample self-selection bias is considered, benchmark regression findings remain substantial.

Table 4. Endogenous test results

	IV			PSM	
	(1)	(2)	(3)	(4)	(5)
	Intelligence	PCM	ExROA	PCM	ExROA
IV1	0.0174*** (0.0032)				
IV2	0.0006*** (0.0002)				
Intelligence		0.0546*** (3.0968)	0.0148*** (2.9870)	0.0034*** (3.0991)	0.0015*** (5.5722)
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk LM statistic		58.785***	58.785***		
Cragg-Donald Wald F statistic		37.927	37.927		
critical values: 10% maximal IV size		19.93	19.93		
Hansen J statistic		0.730	1.726		
R^2		0.427	0.492	0.509	0.504
Observations	14709	14709	14709	14637	14637

Note: Robust t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, and* $p < 0.1$.
Source: By authors.

4.4 Robustness Tests

4.4.1 Replacement of dependent and moderating variables

In this section, Grossprofit and ExROE have been used to replace the dependent variables that are enterprise competitive strength and competitive position, respectively. The column results of the regression are represented in Table 5 (1)-(2). Besides, the ratio of the output value of the tertiary industry to that of the secondary industry in every province (ISS1) is used instead of industrial structure supererogation; and the SR indicator is used instead of industrial structure rationalisation. In contrast to the industrial structure deviation index, the SR indicator shows the significance of each industry accounted for by the means of completing the assignment of the output value. It touches upon the problem of the inverse indicator of the deviation index of the industrial structure and is calculated as follows:

$$SR = -\sum_{i=1}^{n} \left(\frac{Y_i}{Y}\right)\left|\frac{\left(\frac{Y_i}{L_i}\right)}{\left(\frac{Y}{L}\right)} - 1\right|, i \in \{1,2,3\}$$

where Y represents GDP, L represents total national employment, i stands for a particular industry, and n is the total number of industries. A lower SR index indicates greater deviation from equilibrium, whereas a higher SR value signifies a more rational industrial structure. The regression results following the replacement of moderating variables, shown in columns (3)-(6) of Table 5, remain consistent with the baseline findings. In other words, the promotion effect of intelligent manufacturing on the competitive edge of businesses, along with the moderating impact of industrial structure supererogation and rationalisation on this effect, remains significant.

4.4.2 Adding control variables

To minimize the possible omitted variable bias and enhance robustness, some extra control variables such as sales size, institutional investors shareholding ratio, current asset ratio and capital expenditure ratio are introduced. As illustrated in Columns (7)-(8) in Table 5, the fixed-effects regression findings indicate that intelligent manufacturing still has a considerable impact of improving the competitive advantage of firms, as was observed during the baseline.

Table 5. Robustness test results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Grossprofit	ExROE	PCM	ExROA	PCM	ExROA	PCM	ExROA
Intelligence	0.8477^{**} (2.5168)	0.0063^{***} (3.9647)	-0.0037^{*} (-1.7958)	0.0010^{**} (2.0707)	0.0097^{***} (5.9650)	0.0025^{***} (6.2935)	0.0031^{***} (2.8466)	0.0017^{***} (6.0547)
Intelligence× ISS1			0.0043^{***} (3.8657)	0.0004 (1.4206)				
Intelligence× SR					0.0329^{***} (5.5404)	0.0049^{***} (3.0664)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.213	0.598	0.510	0.505	0.510	0.505	0.514	0.505
Observations	14709	14702	14709	14709	14709	14709	14687	14687

Note: Robust t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, and* $p < 0.1$.
Source: By authors.

4.5 Mechanism Tests

Based on the benchmark regression findings, this section goes an extra mile to explore how intelligent manufacturing affects the competitive advantage of firms. It is based on the reasoning provided in the theoretical analysis section that we hypothesize that intelligent manufacturing has a primary impact on the competitive advantage of the businesses in two ways, namely, by increasing production efficiency and information efficiency. A mediating effect model is used to test these propositions.

4.5.1 Production efficiency mechanism tests

The part will look at whether intelligent manufacturing will have an augmentation effect on the competitive advantage of the businesses based on the production efficiency. The LP is applied to measure the total factor productivity, which is used as a proxy measure of the efficiency of enterprise production (TPF LP). Mechanism study of the efficiency of the production is carried out via a mediating effect test and the findings are presented in the columns (1)-(3) of Table 6. The positive relationship between Intelligent Manufacturing and the coefficient of Intelligent Manufacturing (Intelligence) in column (1) has a statistically significant positive relationship at the 1% level, indicating that Intelligent Manufacturing is a significant factor in enhancing efficiency in production of the enterprise. Additionally, the Intelligent Manufacturing (Intelligence) and production efficiency (TFP_LP) coefficients of columns (2) and (3) are significant, which is to indicate that Intelligent Manufacturing enhances the competitive advantage of firms by affecting the production efficiency.

4.5.2 Information efficiency mechanism tests

In this section, the researcher will test the hypothesis on the idea that intelligent manufacturing enhances the competitive advantage of firms by affecting information efficiency. A composite measure of market information asymmetry (ASY) about firms is the index that is used as an inverse measure of information efficiency. In cases that information asymmetry is minimal, firms are more efficient in the transfer and utilisation of information. The Table 6 columns (4)-(6) display the findings of the mediation test of the information efficiency mechanism. The Intelligence, (4) coefficient value is very negative at the 1%, which indicates that the Intelligent manufacturing is a critical aspect in eliminating the information asymmetry both inside and outside the organisation hence allowing efficient transfer of information. The Intelligent Manufacturing (Intelligence) coefficient and the extent of information asymmetry (ASY) in column (5) and (6) are high and this means that intelligent manufacturing enhances the competitive advantage of firms by influencing the efficiency of information.

Table 6. Results of the mechanism tests

	(1)	(2)	(3)	(4)	(5)	(6)
	TFP_LP	PCM	ExROA	ASY	PCM	ExROA
Intelligence	0.0196^{***} (3.4839)	0.0029^{***} (2.6278)	0.0016^{***} (5.9178)	-0.0274^{***} (-3.8072)	0.0033^{***} (2.9481)	0.0017^{***} (6.0266)
TFP_LP		0.0227^{***} (6.7354)	-0.0014^{**} (-2.4652)			
ASY					-0.0085^{***} (-4.9288)	0.0019^{***} (4.0710)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes

Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.531	0.514	0.505	0.299	0.510	0.505
Observations	14665	14665	14665	14709	14709	14709
Sobel test		Z=3.634***	Z=-2.148**		Z=3.418***	Z=-3.072***
Percentage of intermediary effects		0.1332	0.0174		0.0672	0.0329

Note: Robust t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, and* $p < 0.1$.
Source: By authors.

4.6 Heterogeneity Analysis

4.6.1 Heterogeneity in different regional digitisation levels

There is a digitalisation level peer group effect that is expected among enterprises in the same region [58]. The introduction of smart manufacturing can be nurtured and encouraged by the local companies with the help of the regional digital development. The benefit of enterprise intelligent manufacturing is greater in areas with a lower aggregate level of digitisation, which results in a more significant increase in its competitive advantage. Thus, we assume that the impact of enterprise intelligent manufacturing on the competitive advantage is higher in the low-digitisation- regions as compared to the high-digitisation-regions. To verify this hypothesis, the sample enterprises are divided into two groups in terms of the level of digitisation of the province where the individual enterprise is located being less than the median-low digitisation level and high digitisation level. The findings of the grouped regression are presented in table 7. Competitive strength of enterprises is the dependent variable in column (1) and column (2), and the results show that the relationship between intelligent manufacturing and competitive strength of enterprises is significant in the regions where the digitisation level is low. Conversely, in the areas where the level of digitisation is high, the impact of intelligent manufacturing on the competitive strength does not have statistical significance. Going to columns (3) and (4) which take into account the competitive position of the firms, the results indicate that the effect of smart manufacturing on the improvement of the competitive position is present in both groups without statistically significant difference.

Table 7. Heterogeneity test results based on different levels of regional digitisation

	(1)	(2)	(3)	(4)
	Low level of regional digitisation	High level of regional digitisation	Low level of regional digitisation	High level of regional digitisation
	PCM	PCM	ExROA	ExROA
Intelligence	0.0048** (2.5219)	0.0020 (1.4715)	0.0010** (2.0301)	0.0014*** (4.3487)

Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
R^2	0.564	0.458	0.497	0.514
Observations	6652	7969	6652	7969
Coefficients Test of Difference Between Groups p-value			0.102	

Note: Robust t-statistics in parentheses, *** p < 0.01, ** p < 0.05, and* p < 0.1; p-values for tests of differences between groups in coefficients were calculated using the Fisher's Permutation Test (1,000 samples).

Source: By authors.

4.6.2 Heterogeneity in different firms' cost pressures

One of the factors that determine the choices of firms to embrace intelligent manufacturing is its cost pressure. Intelligent manufacturing also helps companies to realize overall information flow and coordination among different business processes including procurement, production, inventory, finance, and sales [18]. This leads to low cost of operation, efficiency in production hence leading to a competitive edge. We postulate that the firm with a greater cost pressure will make high marginal cost reduction with intelligent manufacturing as compared to the firm with a lesser cost pressure hence attaining a higher competitive advantage. To test, the sample enterprises have been divided into two based on their ratio of operating cost being below the industry median. The outcome of the grouped regression is represented in Table 8. In general, smart production contributes to the competitiveness of both categories of companies greatly. Nevertheless, contrary to anticipated effects, the heterogeneous effect of cost pressure varies on the various dimensions of competitive advantage. In particular, the outcomes of the columns (1) and (2) where smart manufacturing is the firm competitive strength, suggest that the effect of intelligent manufacturing on the firm competitive strength is substantial in both groups of differences, and the differences are not significant. When the dependent variable of the model (competitive position) is used in columns (3), and (4), it can be seen that the positive influence of intelligent manufacturing is found in both groups but at a higher extent when using firms that are more pressurized by cost.

Table 8. Heterogeneity test results based on firms' cost pressure

	(1)	(2)	(3)	(4)
	Low-cost pressure	High-cost pressure	Low-cost pressure	High-cost pressure
	PCM	PCM	ExROA	ExROA
Intelligence	0.0048***	0.0031**	0.0011***	0.0019***

	(2.8112)	(2.3676)	(2.6808)	(4.5665)
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
R^2	0.499	0.451	0.503	0.489
Observations	7119	7276	7119	7276
Coefficients Test of Difference Between Groups p-value	0.115		0.005^{***}	

Note: Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, and * p<0.1; p-values for tests of differences between groups in coefficients were calculated using the Fisher's Permutation Test (1,000 samples).
Source: By authors.

6. Conclusions and Implications

6.1 Conclusions

The manufacturing industry is the largest in all of the world, and China is not an exception, experiencing a variety of issues, such as geopolitical tensions, increase in labour costs, low innovation potential, environmental limitations, and the urgent necessity to become digital and smart [59,60,61]. It is important to note that AI is an efficient and promising technology that can improve the performance of manufacturing companies and their competitiveness, which will allow them to overcome these issues. The efficiency in the manufacturing value chain through the deployment of industrial robots, digital twins, blockchain, ChatGPT, and other AI technologies can provide the integration of intelligence at different steps, optimize production processes, enhance quality and efficiency, and increase productivity [62]. This kind of extensive empowerment keeps creating competitive advantages to manufacturing companies [63].

The importance of intelligent manufacturing has been discussed as a strategic aspect, but there is still no extensive theoretical study of how it enhances the competitive advantage of companies, especially through the RBV theory lens. The theoretical background of the study is that, according to RBV, the sustained competitive advantage of a firm lies in its heterogeneous resources, a concept that can be categorised into value, rarity, inimitability, and non- substitutability [29] According to this theoretical background, this study examines the role of intelligent manufacturing as a strategic resource in the formulation of firm-specific competitive advantage in two mechanisms: the resource substitution effect and the resource complementarity effect. Moreover, it examines the moderating nature of industrial structure as complex interrelationships between intelligent manufacturing, industrial structure and competitive advantage are identified. These results can serve as a theoretical contribution and practical advice on creating competitive advantage in the era of intelligent manufacturing.

The empirical findings suggest that the intelligent manufacturing can positively contribute to the product market competitiveness of a firm in two dimensions resource substitution and complementarity. In terms of resource substitutability aspect, the intelligent manufacturing technology can substitute the traditional manufacturing process and the method of transmitting information in a firm, streamline the processes of resource allocation, elevate the efficiency of production process, and improve information processing. This minimizes information asymmetry, costs and enhances competitiveness. Through the introduction of superior technologies that can replace low-skilled labour, intelligent manufacturing also increases productivity, which is aligned with the focus of RBV on the rarity and inimitability of the strategic resources. Based on the issue of resource complementarity, intelligent manufacturing fosters synergy amongst internal resources like technology, human capital, and information and complementarities between itself and external stakeholders. This complement is what increases its flexibility in production and innovation capacity and the effectiveness of collaboration along the supply chain, coordinating the decision-making with suppliers and customers. As a result, this enhances the market responsiveness of the firm. In the RBV theory, such complementarity enhances the entire portfolio of resources, which only adds to its competitive advantage.

In addition to that the research shows that the impact of intelligent manufacturing on competitive advantage is mediated by external industrial structure, regional digitisation, and internal cost pressures. According to RBV, the acquisition and usage of resources are highly reliant on the external conditions. An increased degree of industrial rationalisation and digital infrastructure allow companies to take the resource substitution and complementarity effects of intelligent manufacturing to greater advantage. On the same note, in the presence of high cost pressures, intelligent manufacturing enhances efficiency in the allocation of resources, optimisation of internal operations, cost reduction and competitiveness. These results highlight the explanatory ability of RBV in explaining how intelligent manufacturing is a source of competitive advantage of firms in diverse environmental and organisational settings.

In the future, there are a number of directions which could be expanded. First, to increase the generalisability, the future research can consider the expansion of the analysis to other countries, regions, or small and medium-sized manufacturing companies and investigate the impact of intelligent technologies on the formation of their competitive advantage. Second, the theoretical approaches that may be taken in the future could be different, including the open systems theory or signalling theory, to offer additional points of view. Lastly, future research might divide intelligent manufacturing into dimensions of the breadth and depth of intelligent technology adoption, intelligent capabilities and maturity and thus discuss how certain dimensions of intelligence influence the performance outcomes in manufacturing companies.

6.2 Implications

To begin with, this paper suggests the facilitative aspect of intelligent manufacturing in improving the competitive advantage of firms. The industrial companies ought to, then, struggle hard to embrace smart change so as to enhance their competitiveness. Intelligent manufacturing will enhance production flexibility and efficiency, streamline operations, and promote product innovation internally which leads to value creation. On the outside, it enhances information asymmetry with stakeholders, complementarity of resources, and collaborative decision making, hence the potential of value co-creation.

Second, the paper clarifies that intelligentisation helps to optimise internal and external resources allocation. Based on this, the government agencies must support the formation of information platforms between manufacturing enterprises and the supply chain partners. Underlining the information as the key to intelligent manufacturing will foster information circulation and exchange throughout the industrial chain, as well as the efficiency of resource allocation and the efficiency and collaboration of decisions made.

Third, the results highlight the great role of the industrial structure upgrading and rationalisation on the competitive advantage in intelligent manufacturing. The local governments are thus urged to maximize the industrial environment in the region to facilitate intelligent transformation of firms. It should be aimed at the improvement of infrastructure, industrial structures, the inter-industry coordination, and easy flow of factors of production.

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Conflicts of Interest

The authors confirm that there are no conflicts of interest.

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