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Revolutionizing Chinese Manufacturing: Uncovering the Nexus of Intelligent Transformation and Capital Market Information Efficiency

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Abstract: Intelligent transformation plays a crucial role in advancing sustainable development in manufacturing while also enhancing the information environment. This study examines the role of intelligent transformation in China's manufacturing sector, spanning theoretical and empirical dimensions and being anchored in the context of capital market information efficiency. The theoretical framework highlights how intelligent transformation mitigates information asymmetry, aligning a firm's valuation with its intrinsic value, thereby elevating the information efficiency of capital markets. Leveraging annual reports from China's A-share manufacturing firms, this study employs textual analysis to construct indicators assessing the extent of intelligent transformation across these entities. The empirical findings of this study harmonize with the theoretical constructs. Notably, intelligent transformation emerges as a pivotal driver in enhancing information efficiency in capital markets, substantiated by a negative correlation between intelligent transformation and stock price synchronicity within the manufacturing domain. This correlation withstands a battery of robustness tests and endogeneity treatment. The mechanism driving this transformative impact lies in intelligent transformation's ability to enhance productivity and magnify market attention, thereby positively influencing capital market information efficiency. The insights not only provide empirical support but also offer practical guidance for improving real-world company operations and developing high-quality capital markets.

Keywords: intelligent transformation; manufacturing companies; capital market information efficiency

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1. Introduction

Manufacturing is the core of the industrial sector and an important pillar of national economic development. It promotes not only the development of related industries but also the comprehensive strength of the country [1]. Manufacturing is also an important aspect of industrial competition among countries, and it is a key area for major countries to compete for the upper reaches of the global industrial chain [2]. As the global economic environment and market competition continue to evolve, the intelligent transformation of manufacturing companies is imminent. On the one hand, the global manufacturing industry is becoming increasingly competitive, and the traditional low-cost, low value-added manufacturing model has become unsustainable. Therefore, it is necessary to strengthen the innovation capability and core competitiveness of the manufacturing industry. On the other hand, the innovation of information technology and the reshaping of the industry have a profound impact on the manufacturing industry's development mode and quality. Against the backdrop of the digital economy, promoting the transformation and upgrading of the manufacturing industry to center intelligent manufacturing has become a novel requirement [3]. In December 2021, eight of China's government departments, including the Ministry of Industry and Information Technology and the National Development and Reform Commission, jointly issued the "14th Five-Year Intelligent Manufacturing Development Plan", pointing out that intelligent manufacturing is required to build a manufacturing powerhouse, and that its level of development is directly related to the quality of China's manufacturing industry. The development of intelligent manufacturing plays an important role in consolidating the foundation of the real economy, building a modern industrial system, and achieving a new type of industrialization. In addition, "Made in China 2025" has clearly stated that promoting the intelligent transformation of the manufacturing industry is the only way to achieve a strong manufacturing powerhouse. Therefore, to achieve the high-quality development of manufacturing companies, it is necessary to rely on the support of intelligent transformation, which provides practical significance and a realistic background for this study.

However, intelligent transformation extends beyond being solely an internal revolution within the manufacturing sector. It is closely intertwined with the information efficiency of capital markets, as intelligent transformation alters the information environment of businesses, potentially affecting information mining and the signaling mechanism of capital markets. A central function of capital markets is to facilitate the optimal allocation of resources through information transmission, and information efficiency stands as a critical factor shaping the flow of resources within these markets [4].

China's stock market, however, has historically grappled with information inefficiencies, often characterized by 'noise' and pronounced fluctuations in stock prices [5]. Consequently, enhancing information efficiency has emerged as a pivotal objective in the development of high-quality capital markets. Factors impacting the information efficiency of capital markets encompass external elements, such as the behavior of governmental and institutional investors [6], and internal components, including corporate information transparency and management-level discussions and analysis [7]. Recent studies have explored the influence of emerging technological developments on the information efficiency of capital markets, delving into areas like fintech and smart cities [8,9]. These studies offer a foundational basis for integrating the intelligent transformation of manufacturing into the analytical framework of factors shaping information efficiency within capital markets.

This study seeks to investigate the role of intelligent transformation in the manufacturing industry, commencing with an exploration of its implications for the information efficiency of capital markets. This study attempts to answer two questions: (1) Can enhancements in the information environment of manufacturing companies be effectively transmitted to capital markets, thereby improving their information efficiency? (2) What are the mechanisms and interdependencies through which the intelligent transformation of the manufacturing industry can contribute to the enhancement of information efficiency within capital markets?

This study focuses on the relationship between the manufacturing industry's intelligent transformation and capital market information efficiency, with possible contributions in the following areas. First, this study expands existing research on the economic impact of manufacturing companies' intelligent transformation. While prior research has focused on aspects like innovation or industrial upgrading, there has been a gap in investigating its influence on capital market efficiency. In our study, we seek to fill this gap by examining the impact of the manufacturing industry's intelligent transformation on the information efficiency of capital markets, specifically from the view of manufacturing companies. Through this perspective, we provide micro-level empirical evidence elucidating the economic consequences stemming from this transformation. Second, this study constructs a theoretical model to analyze the internal mechanism of the influence of intelligent transformation on capital market information efficiency. This theoretical model enriches existing theories to some extent and provides potential theoretical support for subsequent micro-level studies of greater depth. Finally, from an empirical perspective, this study finds that improving capital market information efficiency through the intelligent transformation of the manufacturing industry is achieved by improving production efficiency and market attention; this study elucidates its logical mechanism in detail and provides novel research ideas for the relationship between intelligent manufacturing and the information efficiency of capital markets.

2. Literature Review

2.1. Intelligent Manufacturing

“Manufacturing Intelligence” was a pioneering work that introduced the concept of “intelligent manufacturing”, which focuses on the integrated application of robotics [10]. “Manufacturing” is an industrial system, while “intelligence” is a uniquely human attribute. As a product of the deep integration of technology and management [11], intelligent manufacturing should not only follow the laws of industrial development but should also be consistent with the iterative innovation of thinking. With technological development and environmental changes, the connotation of “intelligent manufacturing” has been enriched and refreshed. The Ministry of Industry and Information Technology defines it as a new production method that integrates modern information technology, and this constitutes its most obvious feature. At a deeper level, intelligent manufacturing is a new production method based on new information technology and changes in management concepts, which enable manufacturing enterprises to achieve intelligent production and management, improve quality and efficiency, and contribute to transformative development [12,13].

China’s attention to intelligent manufacturing has gradually increased, and the government has introduced a number of important strategic guidelines to spearhead and guarantee the transformative development of China’s manufacturing industry. In 2015, “Made in China 2025” and “Guiding Opinions on Actively Promoting the ‘Internet+’ Action Plan” were released, which proposed that intelligent manufacturing is the core driver for the transformation and upgrading of the manufacturing industry. In 2017, the State Council issued the “National New Generation Artificial Intelligence Development Plan”, which proposed that intelligent manufacturing is a key application direction in the field of artificial intelligence. Furthermore, in 2020, a digital transformation partnership action plan was released, further emphasizing the key role of intelligent manufacturing in digital transformation. These policy documents have gradually become clear, from their prototype to their completion, in providing a conducive policy environment and policy guidance to accelerate the realization of a digital and intelligent manufacturing industry. In addition, in terms of technological development, the process from informatization to digitalization and then to digital intelligence, the construction of digital information infrastructure, and the promotion of large-scale applications of 5G, big data, artificial intelligence, and other technologies have provided strong technical support for transforming and upgrading the manufacturing industry.

2.2. Intelligent Transformation

The intelligent transformation of a company refers to the application of intelligent technologies to improve its products, services, processes, and organization so that some or all elements and links have intelligent capabilities, thereby realizing the dynamic sensing, interaction, and execution of the internal and external environment [14]. Its connotation is that intelligent transformation can enhance the ability of companies to integrate and exchange information, enabling them to communicate more smoothly with various stakeholders. It can also enhance the ability of companies to mine and integrate internal and external information, helping them become more sensitive to forward-looking technologies and promoting innovation in terms of markets, business models, and technologies [15]. Specifically, companies can use intelligent transformation to upgrade or develop intelligent products or services, enhance product or service innovation, discover new market opportunities, and develop competitive advantages, thereby increasing market share, operating revenues, and performance returns. Intelligent transformation also allows for the optimization of operational processes, the establishment of intelligent decision making and management systems, and improvements in the accuracy and timeliness of decision making. This reduces operating costs, enhances operating efficiency, consolidates core business advantages, and promotes growth in corporate performance [16].

Current academic research on intelligent transformation mainly focuses on two aspects: the motivation for intelligent transformation and the impact of intelligent transformation on companies. The main purpose of companies carrying out intelligent transformation is to reduce the cost of each link and optimize the organizational structure, production, and operation processes [17]. The significant outcome of intelligent transformation for companies is to overcome capital and labor constraints and improve organizational resilience, adaptability, and agility [18]. There are different views on the relationship between intelligent transformation and company development. Some assert that intelligent transformation can empower companies by optimizing their internal division of labor, improving production and operating efficiency, changing value creation models, and visualizing management information [19]. Others believe that intelligent transformation can affect companies by improving innovation models, enhancing innovation capabilities, and reducing innovation risk [20–23]. However, some scholars have highlighted the dynamic, lagging, and heterogeneous impact of intelligent transformation on companies [16].

In general, research on the development of intelligent manufacturing is still in its infancy, with most studies being descriptive analyses of the intelligent development of certain industries or typical enterprises. As a result, the existing research not only appears fragmented and scattered but also lacks quantitative empirical research based on large sample data. Therefore, this study uses a full sample of Chinese manufacturing companies listed on the stock exchange and systematically uncovers the impact of intelligent transformation in Chinese manufacturing companies by mining the textual data of annual reports.

2.3. Information Efficiency of Capital Markets

The information efficiency of capital markets measures the quality of the stock price disclosure of macro-level market, industry, and company-specific information [24]. When capital markets are completely efficient, their information efficiency is optimal [25]. The existing literature states that information disclosure by listed companies has capital market effects [26] and that stock price synchronicity can negatively reflect the degree of disclosure of company-specific information [4,7,27]. In immature emerging capital markets, company-specific information is less integrated into the stock price, resulting in a high degree of stock price synchronicity (i.e., the phenomenon of a "simultaneous increase and decrease" in stock price) [5]. Existing studies indicate that national industrial policies, political relations, corporate governance, social capital, and financial statement transparency [28–31] are significantly associated with stock price synchronicity. Advancements in technology are also an important factor affecting the information efficiency of capital markets. Liu et al. [8] discovered that the development of smart cities can improve the information efficiency of capital markets, whereas Yang et al. [9] pointed out that fintech development also helps to reduce the rate of stock price synchronicity.

Overall, as intelligent transformation gains depth, many scholars have conducted various studies on its motivations and economic consequences. However, there is little research that examines how the intelligent transformation of the manufacturing industry affects the information efficiency of capital markets.

3. Theoretical Model

3.1. Model Design

Referring to Hong and Stein [32] and Zhang et al. [33], this study considered a two-period model where t = 0, 1 for each time period. The entire economy consists of two components, companies, and investors, which are described below.

3.1.1. Companies

The market price (i.e., trading price) of a company is denoted by P_t. In period 0, the company's market price is consistent with its fundamental price, and the market price is recorded as P_0. In period 1, the market price is recorded as P_1. The company's price per share R is randomized with the probability of $\lambda \in (0.5, 1)$ being the high price R_H and the probability of $1 - \lambda$ being the low price R_L. The corporate price is realized in period 0, but it is not directly observable by all participants. Investors estimate the price of a company based on their respective information and engage in trading on that basis.

3.1.2. Investors

The goal of investors is to maximize the price of their holdings, and investors in the market are divided into "informed" and "uninformed" investors based on the amount of information they have access to. All investors are risk-neutral and have a unit demand for the company: d_i^t = 1 or 0 (i = I, U; t = 0,1). Both informed and uninformed investors are intergenerational. In each period, new investors enter the market, actively trade in the market once, and liquidate their corporate positions in the next period.

Before each transaction (t = 0,1,2), a new generation of informed investors can access private signals about the company's price $S_t^I = G,\ \ B$, where G denotes a good signal and B denotes a bad signal, and these signals are rich in information. Companies with high prices will definitely generate good signals, while companies with low prices will generate bad signals with a probability q ∈ (0,1], as shown in Equation (1):

$$Prob\left(S_t^I = B\middle|R = R_L\right) = q \text{ or } Prob\left(S_t^I = G\middle|R = R_H\right) = 1 \quad (1)$$

where q represents the precision of information. In particular, $q \to 0$ implies that a good signal is always obtained, so that this signal has no information content; q = 1 means that a company with high or low price must produce a good or bad signal, respectively, which is completely accurate.

Uninformed investors do not receive private signals; they can only estimate the price of a company from public information. Note that the number of the two types of investors are N^U and N^I, where the number of informed investors is smaller, $N^I < Z$ and the number of uninformed investors is greater, $N^U > Z$.

3.1.3. Intelligent Transformation of Companies

The company's intelligent transformation will be transmitted to the market as a signal from which investors can obtain information about the company's price: D = G, B and $Prob(D = G|R = R_H) = m$ and $Prob(D = B|R = 0) = m$, where $m > 0.5$ and refers to the accuracy of information on the company's intelligent transformation and the company's degree of intelligent transformation. In other words, the greater the extent of a company's intelligent transformation, the more accurate the information it releases.

When investors receive a signal that a company is undergoing intelligent transformation, they observe the signal and then make a judgment about the price of the company. Specifically, the probability that an uninformed investor, who receives a signal of intelligent transformation, believes that the company's price per share is R_H is:

$$\lambda_m \equiv \frac{\lambda m}{\lambda m + (1-\lambda)(1-m)} > \lambda \quad (2)$$

Evidently, λ_m increases with m. The probability that an informed investor, who receives a signal of intelligent transformation, believes that the price of the company is R_H is:

$$\lambda_0 \equiv \frac{\lambda_m}{\lambda_m + (1-\lambda_m)(1-q)} > \lambda_m \quad (3)$$

When the investor receives information on intelligent transformation and considers it to be a bad signal, the investor believes that the price per share of the company must be R_L. Here, $\lambda_0 - \lambda_m$ can be seen as the degree of information asymmetry between informed and uninformed investors, and this difference decreases with m. In other words, as the degree of intelligent transformation increases, the problem of information asymmetry reduces to a greater extent. In particular, when $m \to 1$, $\lambda_0 - \lambda_m$, information asymmetry is completely eliminated.

3.2. Model Analysis

First, we identify the company's market prices in P_0 and P_1, and we solve for the company's market price in P_0. Informed investors will only purchase company stocks when they receive good news. Taking this into account, uninformed investors, knowing that they are more likely to buy a company's stock when the price is lower, will demand a lower price for the company, thus compensating them for their potential losses. Specifically, they demand:

$$\pi_0 \frac{Z}{N^U + N^I}(\lambda_0 R_H - P_0) + (1-\pi_0)\frac{Z}{N^U}(R_L - P_0) \geq 0 \tag{4}$$

In this equation, $\pi_0 \equiv Prob\left(S_0^I = G \middle| D = G\right) = \lambda_m + (1-\lambda_m)(1-q)$ is the probability that an informed investor receives a good signal, $\lambda_0 R_H$ is the expected value of the company's price given a good signal, and $\frac{Z}{N^U+N^I}$ is the probability that an uninformed investor can buy the company's stock at this time. Correspondingly, $1 - \pi_0 = Prob\left(S_0^I = B \middle| D = G\right) = q(1-\lambda_m)$ is the probability that an informed investor receives a bad signal, with the company's price under a bad signal being R_L, and the probability that an uninformed investor can buy the company stock at this time is $\frac{Z}{N^U}$. From the above inequality, the company's market price in P_0 is obtained:

$$P_0 = \frac{\lambda_m R_H}{\lambda_m + (1-\lambda_m)\left(1 + \frac{N^I}{N^U}q\right)} \tag{5}$$

From this equation, it can be observed that $P_0 < \lambda_0 R_H$, indicating that informed investors do buy company stocks in the presence of good signals. Furthermore, $P_0 < \overline{P} \equiv E(R|D = G) = \lambda_m R_H$, which implies that the company's price at P_0 is below the fair market price $\overline{P}$. This phenomenon occurs because of information asymmetry among investors (if $N^I \to 0$, there are no informed investors, and there is no information asymmetry, at which point $P_0 \to \overline{P}$).

Next, the company's price for P_1 is calculated. All investors in this period can observe the number of bidders in P_0 (N^I or $N^U + N^I$) and can thus identify the signals received by informed investors in P_0: S_0^I. Based on this information, if $S_0^I = B$, the price per share of the company is R_L; if $S_0^I = G$, the probability that the price per share is R_H is λ_0.

New informed investors entering P_1 will receive a private signal at S_1^I, in addition to the information from the previous period. If $S_0^I = B$, then S_1^I = B. If $S_0^I = G$, then with probability $\pi_1 = \lambda_0 + (1-\lambda_0)(1-q)$, S_1^I = G and with probability $1 - \pi_1$, $S_1^I = B$. The probability that an informed investor believes that the company's price per share is R_L after observing that $S_1^I = B$, and that of the price per share is R_H after observing that $S_1^I = G$ is:

$$\lambda_1 \equiv \frac{\lambda_0}{\lambda_0 + (1-\lambda_0)(1-q)} > \lambda_0 \tag{6}$$

According to the same steps used when solving for P_0, the following can be obtained:

$$P_1 = \begin{cases} \frac{\lambda_0 R_H}{\lambda_0 + (1-\lambda_0)\left(1+\frac{N^I}{N^U}q\right)} \equiv P_{1G} & \text{If } S_0^I = G \\ 0 & \text{If } S_0^I = B \end{cases} \tag{7}$$

On average, the company's price for P_1 is $\overline{P_1} = \pi_0 P_{1G}$.

Since the stock price is undervalued in P_0 and information is available in P_1, the company's price in this period will converge on average to the fair price $\overline{P_1}$, which is greater than the company's price in P_0. The economics behind this is more intuitive, and the transmission of signals will change the company's price.

Furthermore, this study discusses the relationship between the extent to which a company's share price deviates from its true price $\frac{(\overline{P_1}-P_0)}{P_0}$ and the degree of intelligent transformation. As mentioned earlier, intelligent transformation reduces information asymmetry between informed and uninformed investors, and this effect becomes more pronounced as the level of intelligent transformation increases (i.e., $\lambda_0 - \lambda_m$ decreases with m). The extent to which a company's share price deviates from its true price $\frac{(\overline{P_1}-P_0)}{P_0} = \frac{\overline{P_1}}{P_0} - 1$ is an increasing function of the company's intelligent transformation m since P_0 increases with λ_m. Since $\lambda_0 - \lambda_m$ decreases with m, it can be derived that $(\overline{P_1} - P_0)/P_0$ decreases when m increases. The economic implication is that as the degree of intelligent transformation increases, the closer the price of the company is to its true price. In other words, the company's price reflects all information, unifying its price and value, and the information efficiency of the company's capital markets is also higher at this time.

4. Study Design

4.1. Sample Selection and Data Sources

This study used A-share manufacturing companies listed in China from 2007 to 2020 as the initial research sample and sequentially eliminated ST companies and companies with missing relevant data. Finally, 20,240 company-year data of 2352 listed companies were obtained. To reduce the effect of data outliers on the study results, all continuous variables were shrink-tailed at the 1% and 99% levels.

4.2. Definition and Calculation of Variables

4.2.1. Explained Variable: Information Efficiency of Capital Markets

Drawing on existing studies [4,9], this study used stock price synchronicity (*Scn*) to measure the information efficiency of capital markets.

*Scn*1 is calculated as shown in Equations (8) and (9), where $R_{i,t,j}$ is the weekly individual stock return considering cash dividend reinvestments for company I in week j of year t; $R_{m,t,j}$ is the combined weekly market rate of return considering cash dividend reinvestments for the combined A-share and GEM in week j of year t; $R_{I,t,j}$ is the weekly rate of return for the company's industry (excluding the company) in week j of year t; and $R^2_{i,t}$ is the goodness of fit after regression of Equation (8).

$$R_{i,t,j} = \beta_0 + \beta_1 R_{m,t,j} + \beta_2 R_{I,t,j} + \varepsilon \tag{8}$$

$$Scn1_{i,t} = \ln\left(\frac{R^2_{i,t}}{1 - R^2_{i,t}}\right) \tag{9}$$

Referring to Yi et al. [7], Equation (10) was obtained by adding a one-period lagged composite weekly market rate of return ($R_{m,t-1,j}$) and a one-period lagged industry weekly rate of return ($R_{I,t-1,j}$) to Equation (8). From this, *Scn*2 was calculated using Equations (10) and (11):

$$R_{i,t,j} = \beta_0 + \beta_1 R_{m,t,j} + \beta_2 R_{m,t-1,j} + \beta_3 R_{I,t,j} + \beta_4 R_{I,t-1,j} + \varepsilon \tag{10}$$

$$Scn2_{i,t} = \ln\left(\frac{R^2_{i,t}}{1 - R^2_{i,t}}\right) \tag{11}$$

4.2.2. Explanatory Variable: Intelligent Transformation

A core variable in this study is the degree of intelligent transformation in manufacturing companies. The degree of intelligent transformation is a relatively abstract concept, and it is difficult to identify an indicator that can accurately reflect this concept in reality. To describe manufacturing companies' degree of intelligent transformation as accurately as possible, this study draws on Guo et al.'s research [34]. Based on the textual information of annual reports disclosed by listed manufacturing companies, keywords related to "intelligent transformation" in the annual reports were captured in batches using a Python program, and the total number of occurrences of all keywords in the annual reports was used to construct big data-related variables.

The basic assumptions of this measurement method are that the annual reports disclosed by listed companies are objective statements based on the companies' actual operations, and the number of occurrences of keywords related to intelligent transformation in these reports can better reflect the degree of the companies' intelligent transformation. This study uses the number of times keywords appear in a company's annual report to measure its degree of intelligent transformation. The selection of keywords drew on previous literature, government documents, and industry reports. The definition of intelligent transformation was closely considered, which avoided random selection as much as possible, and data were screened according to the principle of universality. Table 1 shows the keywords related to intelligent transformation, on which the variables used in this study were constructed.

Table 1. Keywords related to intelligent transformation.

Category	Keywords				
Macro Policy	Made in China 2025	Industry 4.0	Internet+		
Paradigm Characteristics	Automation	Informatization	Information Management	Information Application	Digitalization
Enabling Technologies	Networking	Integration	Virtualization	Intelligent	
Key equipment and tools	Internet of Things	Virtual Reality	3D Printing		
Radiation field	Artificial Intelligence	Biometrics	Pattern Recognition	Neural Networks	
	Cloud Computing	Cloud Platform	Cloud Services	Cloud Technology	
	Big Data	Massive Data	Data Center	Data Storage	Data Analysis
	Internet	Mobile Internet	Interconnection	Data Mining	
	Robots	Industrial robots	CNC machine tools	CNC system	Sensors
	Intelligent Logistics	Intelligent Services	Intelligent Terminal	Green Manufacturing	High-end equipment manufacturing
	Smart Grid	Energy Internet	Smart Energy	E-Government	Military–Civilian Integration
	Smart Home	Smart City	Smart Transportation	Smart Healthcare	Smart Community
	New Energy Vehicles	Electric Vehicles	Battery Electric Vehicles	Power Battery	Charging Piles

This study adopted two indicators to measure intelligent transformation. First, im1 is defined as the logarithm of the number of times the keywords related to intelligent transformation were mentioned in the company's annual report plus one. Second, this study also focuses on the frequency density of keywords related to intelligent transformation, and this is denoted by im2, which is the total number of times the keywords related to intelligent transformation appear in the company's annual report divided by the total vocabulary of the annual report (unit: hundred). This reflects the density of words about intelligent transformation in the annual report.

4.2.3. Control Variables

Referring to existing studies, this study controls for the influence of the following factors: return on assets (roa), growth capacity (grevenue), fixed asset ratio (fixed), quick ratio (quick), CEO duality (dual), GEM dummy variable (gem), SOE dummy variable (soe), environmental uncertainty (eu_ind), and equity checks and balances (gov). See Table 2 for specific variable definitions.

Table 2. Variable definition and description.

Variable Category and Name		Variable Symbols	Variable Definition
Explained variables	Stock price synchronicity 1	scn1	The stock price synchronicity index, which measures the information efficiency of the capital market, was obtained from Models (1) and (2)
	Stock price synchronicity 2	scn2	Recalculated stock price synchronicity index after adjusting Model (1)
Explanatory variables	Intelligent transformation 1	im1	Logarithm of total word frequency plus 1
	Intelligent transformation 2	im2	Total word frequency divided by the total number of words in the annual repor×100 (% of intelligent manufacturing)
Control variables	Return on assets	roa	Company's year-end net income to total assets ratio
	Growth capacity	grevenue	Operating income growth rate
	Percentage of fixed assets	fixed	Ratio of net fixed assets to total assets
	Quick ratio	quick	Current assets/current liabilities
	CEO duality	dual	Takes the value of 1 if the chairman and general manager positions are combined into one position, otherwise 0
	GEM dummy variable	gem	Dummy variable, if the company is listed on GEM, takes the value of 1; otherwise, the value is 0
	SOE dummy variable	soe	Dummy variable takes the value of 1 for SOEs, otherwise 0
	Environmental uncertainty	eu_ind	Industry-adjusted environmental uncertainty
	Equity checks and balances	gov	The ratio of the sum of the shareholding of the second to fifth largest shareholders to the shareholding of the largest shareholder at the end of the year

4.3. Model Design

This study tests the impact of manufacturing companies' intelligent transformation on capital market information efficiency using the following benchmark model:

$$\mathrm{scn}_{i,t} = \theta_0 + \theta_1 \mathrm{im}_{i,t} + \theta_2 \mathrm{Controls}_{i,t} + \sum \mathrm{Company} + \varepsilon_{i,t} \quad (12)$$

where $\mathrm{scn}_{i,t}$ is a proxy variable for the information efficiency of capital markets, $\mathrm{im}_{i,t}$ is the shareholding ratio variable for intelligent transformation, $\mathrm{Controls}_{i,t}$ is a control variable defined in Table 2, $\varepsilon_{i,t}$ represents the random error term, and $\sum$Company is a company dummy variable representing a company's fixed effects, with standard errors adjusted for clustering at the company level. This study focuses on the sign of the coefficient θ_1 and its significance, the economic implication of which is the impact of manufacturing companies' intelligent transformation on capital market information efficiency.

5. Empirical Results and Analysis

5.1. Descriptive Statistical Analysis

Table 3 presents the descriptive statistics of the main variables. There were a total of 20,240 company-year observations for manufacturing companies between 2007 and 2020. The mean value of the intelligent transformation index (im1) was 2.8554, the median value was 2.8332, and the standard deviation was 1.3148, which indicates that there were still some differences in intelligent transformation within the sample. The mean values of stock price synchronicity *scn1* and *scn2* were −0.4052 and −0.2359, respectively, which are consistent with the statistics of other companies in the literature.

Table 3. Descriptive statistics.

Variable Name	Sample Size	Average Value	Standard Deviation	Minimum Value	Maximum Value	Median
scn1	20,240	−0.4052	0.8944	−3.2941	1.3839	−0.2558
scn2	20,240	−0.2359	0.7876	−2.4469	1.4722	−0.1114
im1	20,240	2.8554	1.3148	0.0000	5.8406	2.8332
im2	20,240	0.1306	0.1782	0.0000	0.9773	0.0618
roa	20,240	0.0342	0.0537	−0.1754	0.1970	0.0265
grevenue	20,240	0.1643	0.3516	−0.4802	2.1406	0.1118
fixed	20,240	0.2387	0.1422	0.0180	0.6521	0.2119
quick	20,240	2.1172	2.4643	0.2019	15.3158	1.2765
dual	20,240	0.2962	0.4566	0.0000	1.0000	0.0000
gem	20,240	0.1803	0.3844	0.0000	1.0000	0.0000
soe	20,240	0.3292	0.4699	0.0000	1.0000	0.0000
eu_ind	20,240	1.3672	1.5619	0.0158	39.7483	1.0469
gov	20,240	0.7327	0.6151	0.0045	4.0000	0.5749

5.2. Basic Regression

Table 4 presents the regression results of intelligent transformation on the capital market information efficiency. Columns 5 to 8 include control variables based on Columns 1 to 4. The results in Columns 1 to 4 show that regardless of whether *Scn1* or *Scn2* were used as the index of capital market information efficiency, the regression coefficients of intelligent transformation (im1, im2) were both significantly negative at the 1% level. This finding remained unchanged even when adding control variables in Columns 5 to 8. It can be seen that the conclusion that the intelligent transformation of manufacturing companies significantly improves the information efficiency of their capital markets is very robust.

Table 4. Regression results of intelligent transformation and capital market information efficiency.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	**scn1**	**scn2**	**scn1**	**scn2**	**scn1**	**scn2**	**scn1**	**scn2**
im1	−0.0891 ***	−0.0783 ***			−0.0794 ***	−0.0699 ***		
	(−11.72)	(−11.43)			(−10.07)	(−9.84)		
im2			−0.3669 ***	−0.2952 ***			−0.2879 ***	−0.2287 ***
			(−6.13)	(−5.43)			(−4.74)	(−4.17)
roa					−0.1274	−0.2897 **	−0.1732	−0.3285 ***
					(−0.87)	(−2.28)	(−1.18)	(−2.58)
grevenue					−0.1547 ***	−0.1270 ***	−0.1475 ***	−0.1203 ***
					(−7.79)	(−7.36)	(−7.47)	(−7.01)
fixed					0.2608 ***	0.2795 ***	0.3255 ***	0.3390 ***
					(2.89)	(3.56)	(3.58)	(4.27)
quick					0.0171 ***	0.0139 ***	0.0221 ***	0.0186 ***
					(4.26)	(4.14)	(5.40)	(5.45)
dual					0.0294	0.0264	0.0332	0.0299
					(1.34)	(1.36)	(1.50)	(1.53)
gem					−0.2640 **	−0.2218 *	−0.2674 **	−0.2254 **
					(−2.24)	(−1.92)	(−2.28)	(−1.96)
soe					0.0943 *	0.0490	0.1070 **	0.0605
					(1.88)	(1.11)	(2.09)	(1.34)
eu_ind					−0.0026	−0.0025	−0.0042	−0.0040
					(−0.52)	(−0.57)	(−0.83)	(−0.91)
gov					−0.0770 ***	−0.0700 ***	−0.0886 ***	−0.0807 ***
					(−3.44)	(−3.55)	(−3.92)	(−4.05)
Constant	−0.1508 ***	−0.0122	−0.3573 ***	−0.1974 ***	−0.1793 ***	−0.0310	−0.3880 ***	−0.2189 ***
	(−6.95)	(−0.63)	(−45.72)	(−27.79)	(−3.73)	(−0.71)	(−9.25)	(−5.77)
Observations	20,240	20,240	20,240	20,240	20,240	20,240	20,240	20,240
Number of id	2352	2352	2352	2352	2352	2352	2352	2352
Adjusted R-squared	0.008	0.008	0.002	0.002	0.015	0.015	0.010	0.010
Individual fixed effects	Control	Control	Control	Control	Control	Control	Control	Control

Note: The t values in parentheses are adjusted by cluster at the company level; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

5.3. Endogeneity Test

This study mainly examined the impact of intelligent transformation on the information efficiency of manufacturing companies, but there may be endogeneity problems in using the above regression model to identify causal relationships. For the purposes of this study, endogeneity mainly originates from the following sources. The first is reverse causality. Companies with good performance and high valuations have sufficient cash flow and low external financing costs, and they are capable of paying higher costs to invest in intelligent transformation technologies, which in turn leads to an overestimation of the regression coefficients. The second source is omitted variables. There might be factors that are difficult to observe yet are related to companies' intelligent transformation and capital market information efficiency. Therefore, to control for potential endogeneity problems, such as reverse causality and omitted variables, the model was regressed again using two-stage least squares (2SLS) with the lagged terms of intelligent transformation (im1, im2) as instrumental variables.

Columns 1 and 4 of Table 5 show the regression results of the first stage of regression, where the core variables im1 and im2 were regressed on the instrumental variables, and the coefficients of the instrumental variables were found to be significantly positive, which was consistent with expectations. Columns 2, 3, 5, and 6 show the regression results of the second stage. The coefficients of intelligent transformation were still significantly negative, indicating that after dealing with endogeneity problems, intelligent transformation remains significantly related to capital market information efficiency. Therefore, the conclusions of this study still hold.

Table 5. Regression results of instrumental variables.

	Stage I Results	**Stage II Results**	**Stage II Results**	**Stage I Results**	**Stage II Results**	**Stage II Results**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Variables	**im1**	**scn1**	**scn2**	**im2**	**scn1**	**scn2**
L.im1	0.7334 *** (101.61)					
L.im2				0.7555 *** (58.69)		
im1		−0.0952 *** (−8.09)	−0.0902 *** (−8.43)			
im2					−0.3480 *** (−3.76)	−0.3381 *** (−4.02)
roa	0.2050 * (1.88)	0.1309 (0.80)	0.0543 (0.37)	0.0153 (1.12)	0.1678 (1.03)	0.0876 (0.60)
grevenue	0.0353 ** (2.13)	−0.1588 *** (−7.38)	−0.1290 *** (−6.87)	0.0044 ** (2.08)	−0.1554 *** (−7.26)	−0.1259 *** (−6.74)
fixed	−0.4477 *** (−5.32)	0.3449 *** (3.40)	0.3473 *** (3.88)	−0.0409 *** (−5.23)	0.4465 *** (4.43)	0.4423 *** (4.96)
quick	−0.0211 *** (−6.11)	0.0081 (1.60)	0.0048 (1.12)	−0.0033 *** (−6.26)	0.0124 ** (2.44)	0.0088 ** (2.04)
dual	0.0137 (0.82)	0.0212 (0.87)	0.0217 (1.00)	−0.0002 (−0.09)	0.0249 (1.02)	0.0251 (1.15)
gem	−0.0235 (−0.40)	−0.3213 *** (−2.63)	−0.2538 ** (−2.08)	−0.0002 (−0.02)	−0.3237 *** (−2.67)	−0.2559 ** (−2.12)
soe	−0.1263 *** (−2.93)	0.0908 * (1.70)	0.0539 (1.14)	−0.0090 ** (−2.28)	0.1061 * (1.96)	0.0683 (1.43)
eu_ind	0.0123 *** (2.63)	−0.0039 (−0.71)	−0.0031 (−0.62)	0.0003 (0.57)	−0.0055 (−0.99)	−0.0045 (−0.91)
gov	0.0749 *** (3.79)	−0.0677 *** (−2.81)	−0.0664 *** (−3.09)	0.0052 ** (2.26)	−0.0843 *** (−3.50)	−0.0819 *** (−3.81)
Constant	0.9966 *** (22.27)			0.0565 *** (11.70)		
Observations	17,877	17,794	17,794	17,877	17,794	17,794
Number of id	2164	2081	2081	2164	2081	2081
Adjusted R-squared	0.559	−0.117	−0.118	0.585	−0.122	−0.123
Individual fixed effects	Control	Control	Control	Control	Control	Control

Note: Columns 2, 3, 5, and 6 have Z values in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

5.4. Robustness Tests

To ensure the reliability of the main empirical results, the following robustness tests were conducted:5.4.1. Replacing the Measurement Method of Core Explained Variables

Drawing on Morck et al. [27], the weekly industry rate of return $R_{I,t,j}$ was removed from Model (1), and only the weekly individual stock rate of return $R_{i,t,j}$ and the combined weekly market rate of return $R_{m,t,j}$ were retained to obtain Model (5). The specific calculation steps are shown in Equations (12) and (13):

$$R_{i,t,j} = \beta_0 + \beta_1 R_{m,t,j} + \varepsilon \tag{13}$$

$$Syn_{i,t} = \ln\left(\frac{R_{i,t}^2}{1 - R_{i,t}^2}\right) \tag{14}$$

The calculated stock price synchronicity index *Scn3* was used as a proxy variable of capital market information efficiency for regression. Columns 1 and 2 of Table 6 present the regression results, which show that intelligent transformation (im1, im2) remains significantly and negatively correlated with *Scn3.* This is consistent with previous findings, indicating that the conclusion that intelligent transformation can improve the information efficiency of capital markets is independent of the calculation method of the stock price synchronicity index, thereby further validating the research hypothesis.

Table 6. Robustness test: regression results of intelligent transformation and capital market information efficiency.

	(1)	(2)	(3)	(4)
Variables	**scn3**	**scn3**	**scn1**	**scn2**
im1	−0.0767 ***			
	(−7.85)			
im2		−0.1674 **		
		(−2.29)		
im3			−0.0986 ***	−0.0869 ***
			(−11.45)	(−11.14)
roa	−1.2303 ***	−1.2681 ***	−0.1198	−0.2829 **
	(−6.31)	(−6.50)	(−0.81)	(−2.23)
grevenue	−0.1821 ***	−0.1736***	−0.1543 ***	−0.1267 ***
	(−7.02)	(−6.72)	(−7.79)	(−7.36)
fixed	0.1355	0.2095*	0.2586 ***	0.2774 ***
	(1.17)	(1.81)	(2.88)	(3.55)
quick	0.0257 ***	0.0319 ***	0.0176 ***	0.0143 ***
	(4.86)	(5.98)	(4.42)	(4.31)
dual	0.0444	0.0487*	0.0274	0.0246
	(1.57)	(1.70)	(1.26)	(1.28)
gem	−0.4489 ***	−0.4548 ***	−0.2724 **	−0.2292 **
	(−3.17)	(−3.22)	(−2.32)	(−1.99)
soe	0.1811 ***	0.1945 ***	0.0916 *	0.0466
	(2.87)	(3.03)	(1.83)	(1.06)
eu_ind	0.0098	0.0080	−0.0028	−0.0027
	(1.52)	(1.23)	(−0.55)	(−0.61)
gov	−0.0225	−0.0359	−0.0770 ***	−0.0700 ***
	(−0.81)	(−1.29)	(−3.44)	(−3.55)
Constant	−0.6531 ***	−0.8735 ***	−0.1571 ***	−0.0110
	(−10.71)	(−16.26)	(−3.33)	(−0.26)
Observations	20,240	20,240	20,240	20,240
Number of id	2352	2352	2352	2352
Adjusted R-squared	0.014	0.011	0.017	0.016
Individual fixed effects	Control	Control	Control	Control

Note: The t values in parentheses are adjusted by cluster at the company level; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

5.4.1. Replacing the Measurement Method of Core Explanatory Variables

There may be some noise in the word frequency data. Hence, categorical variables were constructed in this study. Sorting the frequency of words related to intelligent transformation from smallest to largest and dividing them into four quartiles, the categorical variables take the value of 1 for the first quartile of observations, 2 for the second quartile, 3 for the third quartile, and 4 for last quartile. The regression results are presented in Columns 3 and 4 of Table 6, showing that the results after replacing the indicator for intelligent transformation were robust.

5.4.2. Model Specification Adjustment

The model employed in this study is the individual fixed effects model. To ensure the robustness of our results, we have employed multiple alternative methods. Specifically, we have re-designed the fixed effects model by introducing industry and province fixed effects. The utilization of industry × province fixed effects is aimed at controlling for the influence of unobservable factors that vary across different industries and provinces.

Columns (1)–(4) of Table 7 encompass the control of industry and province fixed effects, while columns (5)–(8) introduce industry and province interaction fixed effects. The results presented in Table 7 indicate that intelligent transformation significantly reduces stock price synchronicity and enhances capital market information efficiency. This further validates the robustness of our baseline results.

Table 7. Robustness test.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	**scn1**	**scn2**	**scn1**	**scn2**	**scn1**	**scn2**	**scn1**	**scn2**
im1	−0.0490 ***	−0.0361 ***			−0.0497 ***	−0.0369 ***		
	(−8.34)	(−7.02)			(−8.41)	(−7.13)		
im2			−0.1174 ***	−0.0641 *			−0.1193 ***	−0.0652 *
			(−2.83)	(−1.75)			(−2.87)	(−1.77)
roa	0.0802	−0.0328	0.0652	−0.0377	0.0707	−0.0433	0.0558	−0.0480
	(0.62)	(−0.28)	(0.50)	(−0.33)	(0.55)	(−0.38)	(0.43)	(−0.42)
grevenue	−0.1533 ***	−0.1266 ***	−0.1516 ***	−0.1263 ***	−0.1529 ***	−0.1265 ***	−0.1511 ***	−0.1261 ***
	(−8.04)	(−7.70)	(−7.97)	(−7.70)	(−7.99)	(−7.66)	(−7.91)	(−7.65)
fixed	0.2922 ***	0.2955 ***	0.3661 ***	0.3599 ***	0.2978 ***	0.3020 ***	0.3732 ***	0.3684 ***
	(4.68)	(5.29)	(5.89)	(6.49)	(4.71)	(5.34)	(5.93)	(6.58)
quick	0.0130 ***	0.0095 ***	0.0163 ***	0.0120 ***	0.0131 ***	0.0096 ***	0.0165 ***	0.0123 ***
	(4.48)	(3.94)	(5.59)	(5.01)	(4.48)	(3.98)	(5.62)	(5.09)
dual	−0.0190	−0.0236 *	−0.0194	−0.0245 *	−0.0177	−0.0225	−0.0181	−0.0233
	(−1.16)	(−1.68)	(−1.18)	(−1.73)	(−1.08)	(−1.59)	(−1.10)	(−1.64)
gem	−0.0657 ***	−0.0600 ***	−0.0852 ***	−0.0765 ***	−0.0640 ***	−0.0585 ***	−0.0836 ***	−0.0752 ***
	(−3.09)	(−3.38)	(−4.07)	(−4.38)	(−2.98)	(−3.26)	(−3.96)	(−4.27)
soe	0.2332 ***	0.1912 ***	0.2431 ***	0.1985 ***	0.2333 ***	0.1918 ***	0.2435 ***	0.1995 ***
	(10.91)	(10.08)	(11.36)	(10.48)	(10.80)	(10.01)	(11.27)	(10.43)
eu_ind	−0.0064	−0.0074 **	−0.0061	−0.0069 *	−0.0059	−0.0069 *	−0.0058	−0.0065 *
	(−1.44)	(−1.99)	(−1.38)	(−1.84)	(−1.33)	(−1.82)	(−1.29)	(−1.71)
gov	−0.0620 ***	−0.0535 ***	−0.0663 ***	−0.0563 ***	−0.0637 ***	−0.0552 ***	−0.0683 ***	−0.0582 ***
	(−4.81)	(−4.79)	(−5.13)	(−5.04)	(−4.91)	(−4.91)	(−5.24)	(−5.17)
Constant	−0.2333	−0.0653	−0.3602*	−0.1626	−0.2366 ***	−0.1430 ***	−0.4602 ***	−0.3223 ***
	(−1.21)	(−0.43)	(−1.85)	(−1.08)	(−4.80)	(−3.30)	(−11.11)	(−8.86)
Observations	20,240	20,240	20,240	20,240	20,240	20,240	20,240	20,240
Adjusted R-squared	0.013	0.012	0.009	0.008	0.014	0.012	0.009	0.008
Industry FE	Control	Control	Control	Control	-	-	-	-
Province FE	Control	Control	Control	Control	-	-	-	-
Industry × Province FE	-	-	-	-	Control	Control	Control	Control

Note: The t values in parentheses are adjusted by cluster at the company level; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

6. Analysis of the Impact Mechanism

The preceding analysis supports the idea that intelligent transformation can promote the information efficiency of capital markets, but the mechanism behind its impact has yet to be examined. In this study, we tested two mechanism pathways based on production efficiency and market attention.

6.1. Pathway Test Based on Production Efficiency

To test whether the channels for improving production efficiency were effective, referring to Lu and Lian [35], this study used total factor productivity (TFP) to measure the company's production efficiency and examine how intelligent transformation impacts it. Considering the existence of problems such as sample selection bias, model assumption requirements, endogeneity, and estimation uncertainty, this study applied parametric and semi-parametric methods such as the least squares, fixed effects, OP, and LP methods to calculate the TFP of manufacturing companies in China. The TFP under different calculation methods was regressed as the explained variable. Table 8 shows the regression results of TFP on im1 using different methods, which indicate that the estimated coefficient of im1 was significantly positive. This shows that intelligent transformation has helped companies significantly improve their own production efficiency. The explanatory variable in Table 9 is im2, and the results corroborate the findings in Table 8: intelligent transformation enhances capital market information efficiency by promoting the companies' production efficiency.

Table 8. Pathway test: improving production efficiency (im1).

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Variables	**tfp_ols**	**tfp_fe**	**tfp_lp**	**tfp_op**	**tfp_gmm**
im1	0.9332 ***	0.9815 ***	0.7029 ***	0.5731 ***	0.3036 ***
	(30.73)	(30.72)	(30.20)	(31.06)	(28.21)
roa	20.7001 ***	21.6622 ***	16.3384 ***	13.3170 ***	8.3148 ***
	(28.38)	(28.29)	(28.76)	(29.45)	(30.61)
grevenue	−0.5448 ***	−0.5801 ***	−0.3815 ***	−0.2851 ***	−0.0959 ***
	(−9.24)	(−9.38)	(−8.35)	(−7.64)	(−4.21)
fixed	3.0985 ***	3.3897 ***	1.4598 ***	1.2240 ***	−0.7778 ***
	(9.69)	(10.09)	(5.89)	(6.09)	(−6.24)
quick	−0.4751 ***	−0.4993 ***	−0.3670 ***	−0.2882 ***	−0.1651 ***
	(−20.82)	(−20.84)	(−20.74)	(−20.39)	(−19.67)
dual	−0.2013 ***	−0.2100 ***	−0.1575 ***	−0.1393 ***	−0.0866 ***
	(−2.84)	(−2.82)	(−2.88)	(−3.15)	(−3.29)
gem	0.0080	0.0076	0.0048	0.0168	0.0077
	(0.03)	(0.03)	(0.02)	(0.11)	(0.08)
soe	0.3649 ***	0.3843 ***	0.2896 ***	0.2048 **	0.1268 **
	(2.61)	(2.62)	(2.67)	(2.20)	(2.09)
eu_ind	0.0572 ***	0.0605 ***	0.0396 ***	0.0342 ***	0.0124 *
	(3.50)	(3.53)	(3.11)	(3.26)	(1.78)
gov	−0.3087 ***	−0.3240 ***	−0.2459 ***	−0.1832 ***	−0.1127 ***
	(−4.81)	(−4.81)	(−4.91)	(−4.46)	(−4.28)
Constant	6.5600 ***	6.8685 ***	5.2585 ***	4.0816 ***	2.6243 ***
	(36.58)	(36.46)	(37.92)	(36.61)	(38.88)
Observations	20,240	20,240	20,240	20,240	20,240
Number of id	2352	2352	2352	2352	2352
Adjusted R-squared	0.285	0.285	0.280	0.283	0.274
Industry fixed effects	Control	Control	Control	Control	Control

Note: The t values in parentheses are adjusted by cluster at the company level; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 9. Pathway test: improving production efficiency (im2).

	(1)	(2)	(3)	(4)	(5)
Variables	**tfp_ols**	**tfp_fe**	**tfp_lp**	**tfp_op**	**tfp_gmm**
im2	5.5698 ***	5.8578 ***	4.2022 ***	3.4131 ***	1.8180 ***
	(20.56)	(20.56)	(20.28)	(20.73)	(19.05)
roa	21.3637 ***	22.3601 ***	16.8385 ***	13.7241 ***	8.5310 ***
	(28.80)	(28.71)	(29.17)	(29.88)	(31.02)
grevenue	−0.6002 ***	−0.6384 ***	−0.4231 ***	−0.3192 ***	−0.1138 ***
	(−10.13)	(−10.27)	(−9.22)	(−8.51)	(−4.98)
fixed	2.5653 ***	2.8290 ***	1.0590 ***	0.8958 ***	−0.9506 ***
	(8.05)	(8.45)	(4.31)	(4.47)	(−7.71)
quick	−0.5057 ***	−0.5315 ***	−0.3900 ***	−0.3071 ***	−0.1749 ***
	(−21.70)	(−21.72)	(−21.62)	(−21.27)	(−20.53)
dual	−0.2322 ***	−0.2425 ***	−0.1808 ***	−0.1584 ***	−0.0966 ***
	(−3.07)	(−3.05)	(−3.11)	(−3.37)	(−3.49)
gem	−0.0022	−0.0031	−0.0031	0.0107	0.0042
	(−0.01)	(−0.01)	(−0.01)	(0.06)	(0.04)
soe	0.2378	0.2506 *	0.1939 *	0.1267	0.0855
	(1.64)	(1.65)	(1.71)	(1.32)	(1.36)
eu_ind	0.0714 ***	0.0755 ***	0.0503 ***	0.0430 ***	0.0170 **
	(3.97)	(4.00)	(3.63)	(3.78)	(2.35)
gov	−0.2153 ***	−0.2258 ***	−0.1757 ***	−0.1257 ***	−0.0825 ***
	(−3.11)	(−3.11)	(−3.30)	(−2.87)	(−3.05)
Constant	8.6403 ***	9.0565 ***	6.8241 ***	5.3606 ***	3.2999 ***
	(61.26)	(61.17)	(62.46)	(59.93)	(59.32)
Observations	20,240	20,240	20,240	20,240	20,240
Number of id	2352	2352	2352	2352	2352
Adjusted R-squared	0.252	0.252	0.249	0.250	0.248
Individual fixed effects	Control	Control	Control	Control	Control

Note: The t values in parentheses are adjusted by cluster at the company level; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

6.2. Pathway Test Based on Market Attention

This study used news media exposure to test the mechanism of market attention on intelligent transformation. Attention1 is the ratio of the volume of company-related news to the total volume of news for the year multiplied by 100, while attention2 is the natural logarithm of the number of company-related news in that year plus one. As shown in Table 10, the values of im1 and im2 were significantly positive for both attention1 and attention2, which indicates that intelligent transformation can indeed improve capital market information efficiency by promoting market attention. In summary, intelligent transformation positively affects capital market information efficiency by increasing manufacturing companies' production efficiency and market attention, enhancing their information transparency, and reducing information asymmetry. Specifically, intelligent transformation can improve companies' production efficiency and quality and reduce production costs, thus enhancing their competitiveness and garnering more attention and recognition from the market. At the same time, intelligent transformation can also improve the transparency of information and companies' data collection capabilities, allowing investors to more accurately understand the company's operating conditions, financial situation, and future development prospects. In this way, the true value of the company is more easily recognized by the market, and the information efficiency of the capital market will also be enhanced. Thus, intelligent transformation has a positive effect on capital market information efficiency, as it increases production efficiency and market attention.

Table 10. Pathway test: increasing market attention.

	(1)	(2)	(3)	(4)
Variables	**attention1**	**attention2**	**attention1**	**attention2**
im1	0.0025 ***	0.5578 ***		
	(34.18)	(53.35)		
im2			0.0151 ***	3.2718 ***
			(21.91)	(29.01)
roa	−0.0024	−0.3258	−0.0006	0.0675
	(−1.52)	(−1.22)	(−0.38)	(0.23)
grevenue	0.0004**	0.0443	0.0002	0.0104
	(2.07)	(1.40)	(1.24)	(0.32)
fixed	−0.0036 ***	−0.8462 ***	−0.0049 ***	−1.1708 ***
	(−4.83)	(−6.00)	(−5.96)	(−6.99)
quick	−0.0003 ***	−0.0643 ***	−0.0003 ***	−0.0834 ***
	(−7.32)	(−9.51)	(−8.69)	(−11.03)
dual	−0.0006 ***	−0.0748 *	−0.0007 ***	−0.0936 **
	(−2.64)	(−1.93)	(−2.83)	(−2.18)
gem	0.0008	0.2581 **	0.0007	0.2533 *
	(1.20)	(2.07)	(1.13)	(1.94)
soe	−0.0025 ***	−0.3657 ***	−0.0028 ***	−0.4423 ***
	(−4.88)	(−4.59)	(−5.01)	(−4.81)
eu_ind	0.0001 ***	0.0265 ***	0.0002 ***	0.0351 ***
	(2.60)	(2.73)	(2.91)	(3.03)
gov	0.0016 ***	0.2800 ***	0.0018 ***	0.3370 ***
	(7.25)	(7.22)	(7.57)	(7.41)
Constant	−0.0022 ***	−0.3267 ***	0.0032 ***	0.9266 ***
	(−5.32)	(−4.65)	(8.17)	(12.46)
Observations	20,240	20,240	20,240	20,240
Number of id	2352	2352	2352	2352
Adjusted R-squared	0.123	0.150	0.084	0.095
Individual fixed effects	Control	Control	Control	Control

Note: The t values in parentheses are adjusted by cluster at the company level; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

7. Discussion

Intelligent transformation brings great changes to both business and national development. Our study aligns with the growing recognition that intelligent transformation is emerging as a key driver of the Fourth Industrial Revolution. As highlighted in previous studies [17,23], the primary objective of firms embarking on intelligent transformation is to achieve a cost reduction across various operational facets while simultaneously optimizing organizational structures and production processes.

Moreover, the effects of intelligent transformation extend to overcoming constraints associated with capital and labor, as noted by Sussan and Acs (2017) [18]. Research in this domain has yielded perspectives regarding the relationship between intelligent transformation and firm development. Some scholars emphasize the empowerment of firms through mechanisms such as optimizing internal division of labor, improving production operational efficiency, altering value creation models, and enabling visualized management information [19]. Others contend that intelligent transformation influences firms by enhancing innovation patterns, bolstering innovation capabilities, and mitigating innovation risks [20–22].

Our study contributes to this body of research by exploring a critical influence of intelligent transformation: its impact on capital market information efficiency within the context of manufacturing firms. While prior studies have offered valuable insights into the broader effects of intelligent transformation, fewer have examined whether intelligent transformation plays a substantial role in enhancing the capital market efficiency of manufacturing firms.

Intelligent transformation can improve the transparency of information and companies' data collection capabilities, allowing investors to better understand the companies' operating conditions, financial situations, and future development prospects and to judge their value more objectively. At the same time, intelligent transformation directly improves companies' information environment and provides space for development and application scenarios in which data production factors can leverage governance functions through "industrial digitization" and "digital industrialization".

The key findings of this study are as follows. First, our theoretical model has demonstrated that intelligent transformation plays a crucial role in reducing information asymmetry. This reduction leads to a closer alignment of firm stock prices with their true intrinsic values, thereby significantly enhancing capital market information efficiency. The theoretical framework underscores the importance of intelligent transformation as a mechanism for promoting transparency and accuracy in stock pricing.

Second, the empirical test finds that intelligent transformation helps to reduce manufacturing companies' stock price synchronicity and improve capital market information efficiency. The data dividend released by intelligent transformation promotes the interconnection of information from all parties, which in turn promotes the timely integration of company-specific information into stock prices.

Finally, the mechanism tests show that intelligent transformation can improve companies' production efficiency and market attention to reduce their stock price synchronicity and improve capital market information efficiency. Intelligent transformation provides companies with more development opportunities and application scenarios while also improving their governance efficiency and market competitiveness. Intelligent transformation also broadens access to information for companies and investors and exerts the effects of information governance. The above two mechanisms together facilitate the mining and transmission of in-depth information about companies.

8. Recommendations

This paper explores the relationship between intelligent transformation and the information efficiency of capital markets within the context of manufacturing firms. Unlike previous analyses, our paper, as far as we know, provides the first empirical study on how intelligent transformation influences the capital markets information efficiency.

This study has the following implications for policymakers, industry stakeholders, and businesses. First, deepening intelligent transformation in manufacturing: To promote the digital economy and unlock digital dividends, it is imperative to further the intelligent transformation of the manufacturing industry. This transformation should be accompanied by efforts to strengthen data collaboration and sharing among stakeholders, thereby fostering an improved digital ecosystem. A conducive digital environment will not only benefit businesses but also enhance the information environment for companies conducting business, ultimately driving economic growth.

Second, enhancing information transparency and governance: There is a critical need to improve the design of systems and regulations to break down information barriers. Scientific supervision should be introduced to ensure transparency and fairness in capital markets. This includes enhancing supervision of media and public opinion to collectively create a sustainable and trustworthy business information environment, instilling investor confidence.

Finally, adapting to the digital economy: Manufacturing companies should follow the development trend of the digital economy. They should engage in internal innovation and reform, leveraging digital empowerment to optimize corporate governance and information disclosure mechanisms. By doing so, companies can maximize their corporate value and competitiveness in a rapidly evolving digital landscape.

Intelligent transformation is a highly complex topic. Our study primarily focuses on the impact of intelligent transformation on publicly listed manufacturing companies, making it challenging to generalize the effects on small and medium-sized enterprises (SMEs).

Further research is needed to examine how intelligent transformation affects the capital market information efficiency of SMEs, given their unique characteristics and challenges. Secondly, our investigation primarily focuses on the manufacturing sector, and we have not explored the implications of intelligent transformation on non-manufacturing sectors. It remains an important field for future research to determine whether intelligent transformation can similarly enhance capital market information efficiency for non-manufacturing companies.

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References

1. Zhou, J. Intelligent Mannfacturing-Main Direction of "Made in China 2025". *Chin. Mech. Eng.* **2015**, *26*, 2273–2284.
2. Yang, R.D. Study on the Total Factor Productivity of Chinese Manufacturing Enterprises. *Econ. Res. J.* **2015**, *50*, 61–74. Available online: https://kns.cnki.net/kcms2/article/abstract?v=BBImVa1yplt2tcAKXPrlRrm52R1UX4yf4X73xzKIC5qKKJBh5bKlrMq9WUWMU8iyu5NMDkpp27PMxZ4mJNy_f0_SljUQRzAYcdILEmMSEFtru68e30jdq_eI8DPPozmdlbF4bA8eVc0=&uniplatform=NZKPT&language=CHS (accessed on 27 September 2023).
3. Ma, S.Z.; Fang, C.; Liang, Y.F. Digital Trade and Its Era Value and Research Prospects. *J. Int. Trade* **2018**, *10*, 16–30. [CrossRef]
4. Zhu, J. The Belt and Road Initiative and the Information Efficiency of Capital Market. *Bus. Manag. J.* **2019**, *41*, 38–56. [CrossRef]
5. Zhu, H.J.; He, X.J.; Tao, L. Can stock analysts in China improve the efficiency of capital markets—Empirical evidence based on stock price synchronicity and stock price information content. *J. Financ. Res.* **2007**, *02*, 110–121. Available online: https://kns.cnki.net/kcms/detail/detail.aspx?FileName=JRYJ200702010&DbName=CJFQ2007 (accessed on 27 September 2023).
6. Chen, D.H.; Yao, Z.Y. Will Government Behavior Definitely Increase Stock Price Synchronicity? Empirical Evidence from China's Industrial Policies. *Econ. Res. J.* **2018**, *53*, 112–128. Available online: https://kns.cnki.net/kcms/detail/detail.aspx?FileName=JJYJ201812009&DbName=CJFQ2018 (accessed on 27 September 2023).
7. Yin, Z.H.; Yang, S.Z.; Chen, Q.Y. Could Analysts Reduce Stock Price Synchronicity—A Textual Analysis Based on Analyst Report. *China Ind. Econ.* **2019**, *01*, 156–173. [CrossRef]
8. Liu, T.L.; Wang, Y.; Yang, S.L. Can Smart City Construction Improve the Information Efficiency of Capital Market? *J. Beijing Technol. Bus. Univ. (Soc. Sci.)* **2022**, *37*, 33–43. Available online: https://kns.cnki.net/kcms/detail/detail.aspx?FileName=BJSB202204004&DbName=CJFQ2022 (accessed on 27 September 2023).
9. Yang, S.L.; Liu, M.W.; Zhang, Q.Y. Impact of China's Fintech Development on Information Efficiency of Capital Market. *J. Quant. Tech. Econ.* **2021**, *38*, 125–144. [CrossRef]
10. Manufacturing intelligence: P., K. Wright and D. A. Bourne, Addison-Wesley, Reading, Mass.: 1988. Reviewed by S. H. Kim. In *Robotics and Computer-Integrated Manufacturing*; Elsevier: Amsterdam, The Netherlands, 1988; Volume 4, p. 293. [CrossRef]
11. Kang, H.S.; Lee, J.Y.; Choi, S.S.; Kim, H.; Park, J.H.; Son, J.Y.; Kim, B.H.; Noh, S.D. Smart manufacturing: Past research, present findings, and future directions. *Int. J. Precis. Eng. Manuf. Green Technol.* **2016**, *3*, 111–128. [CrossRef]
12. Culot, G.; Nassimbeni, G.; Orzes, G.; Sartor, M. Behind the definition of Industry 4.0: Analysis and open questions. *Int. J. Prod. Econ.* **2020**, *226*, 107617. [CrossRef]
13. Yang, J.; Ying, L.M.; Gao, M.R. The influence of intelligent manufacturing on financial performance and innovation performance: The case of China. *Enterp. Inf. Syst.* **2020**, *14*, 788–803. [CrossRef]
14. Baqee, D.R.; Farhi, E. The Macroeconomic Impact of Microeconomic Shocks: Beyond Hulten's Theorem. *Econometrica.* **2019**, *87*, 1155–1203. [CrossRef]
15. Meng, F.S.; Zhao, G. Empirical Research on the Relationship between Innovation Flexibility and Intelligent Transformation of Chinese Manufacturing Enterprises—The Mediation and Moderation of Business Model Innovation and Environmental Dynamics. *Int. J. Forecast.* **2018**, *37*, 1–8. Available online: https://kns.cnki.net/kcms/detail/detail.aspx?FileName=YUCE201806001&DbName=CJFQ2018 (accessed on 27 September 2023).
16. Xuan, Y.; Zhang, W.L. The Micro Mechanism of Intelligence on Enterprise Production Performance:The Example of Capacity Utilization and Profit. *Sci. Sci. Manag. S.& T.* **2021**, *42*, 96–119. Available online: https://kns.cnki.net/kcms/detail/detail.aspx?FileName=KXXG202111006&DbName=DKFX2021 (accessed on 27 September 2023).

17. Wang, B.; Wang, Q.C. Total factor productivity, resource mismatch and industrial intelligence strategy —An analysis based on Guangdong enterprises. *Soc. Sci. Guangdong* **2019**, *05*, 17–26. Available online: https://kns.cnki.net/kcms/detail/detail.aspx?FileName=GDSK201905002&DbName=CJFQ2019 (accessed on 27 September 2023).
18. Sussan, F.; Acs, Z.J. The digital entrepreneurial ecosystem. *Small Bus. Econ.* **2017**, *49*, 55–73. [CrossRef]
19. Nadkarni, S.; Prügl, R. Digital transformation: A review, synthesis and opportunities for future research. *Manag. Rev. Q.* **2020**, *71*, 233–341. [CrossRef]
20. Deng, Y.; Jiang, W.Y. Does Frontier Technology Promote Enterprise Innovation? Explanation Based on Labor Diversity of Manufacturing Force. *Reform* **2022**, *9*, 108–122. Available online: https://kns.cnki.net/kcms/detail/detail.aspx?FileName=REFO202209009&DbName=CJFQ2022 (accessed on 27 September 2023).
21. Yang, S.Y.; Wang, W.Z.; Ding, T. Intelligent transformation and sustainable innovation capability: Evidence from China. *Financ. Res. Lett.* **2023**, *55*, 103963. [CrossRef]
22. Han, J.; Jiang, C.l.; Liu, R. Does intelligent transformation trigger technology innovation in China's NEV enterprises? *Energy* **2023**, *270*, 126823. [CrossRef]
23. Shen, A.H.; Wang, R. Digital Transformation and Green Development Research: Microscopic Evidence from China's Listed Construction Companies. *Sustainability.* **2023**, *15*, 12481. [CrossRef]
24. Piotroski, J.D.; Roulstone, D.T. The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices. *Acc. Rev.* **2004**, *79*, 1119–1151. Available online: https://kns.cnki.net/kcms/detail/detail.aspx?FileName=SJSTA4D481E9F63BE2E853B5CE4C82DC645F&DbName=GARJ0010_1 (accessed on 27 September 2023). [CrossRef]
25. Schwartz, R.A. Efficient capital markets: A Review of Theory and Empirical Work. *J. Financ.* **1970**, *25*, 383–417. [CrossRef]
26. Wu, H.; Tian, G.L.; Si, Y.; Yu, Z.B. Internet Media Management and Stock Liquidity. *J. Manag. Sci.* **2017**, *30*, 51–64. Available online: https://kns.cnki.net/kcms/detail/detail.aspx?FileName=JCJJ201706005&DbName=CJFQ2017 (accessed on 27 September 2023).
27. Morck, R.; Yeung, B.; Yu, W. The information content of stock markets: Why do emerging markets have synchronous stock price movements? *J. Financ. Econ.* **2000**, *58*, 215–260. [CrossRef]
28. Gul, F.A.; Kim, J.B.; Qiu, A.A. Ownership concentration, foreign shareholding, audit quality, and stock price synchronicity: Evidence from China. *J. Financ. Econ.* **2010**, *95*, 425–442. [CrossRef]
29. Hutton, A.P.; Marcus, A.J.; Tehranian, H. Opaque financial report, R2, and crash risk. *J. Financ. Econ.* **2009**, *94*, 67–86. [CrossRef]
30. Gao, B.; Zhang, J.L.; Xie, J.; Zhang, W.J. The impact of carbon risk on the pricing efficiency of the capital market: Evidence from a natural experiment in China. *Financ. Res. Lett.* **2023**, *57*, 104268. [CrossRef]
31. Hsin, C.W.; Peng, S.C. The role of social capital in price efficiency: International evidence. *Int. Rev. Financ. Anal.* **2023**, *89*, 102740. [CrossRef]
32. Hong, H.; Stein, J.C. Disagreement and the stock market. *J. Econ. Perspect.* **2007**, *21*, 109–128. Available online: https://www.aeaweb.org/articles?id=10.1257/jep.21.2.109 (accessed on 27 September 2023). [CrossRef]
33. Zhang, X.Y.; Chen, R.; Wei, X. Underwriters and Re-IPO performance. *Econ. Res. J.* **2020**, *55*, 164–180. Available online: https://kns.cnki.net/kcms/detail/detail.aspx?FileName=JJYJ202001012&DbName=CJFQ2020 (accessed on 27 September 2023).
34. Guo, L.; He, F.B.; Li, J.W. Analysis on the Development Trend of Intelligent Manufacturing in China—A Text Analysis Based on Annual Reports of Listed Manufacturing Firms. *Innov. Sci. Technol.* **2020**, *20*, 61–71. [CrossRef]
35. Lu, X.D.; Lian, Y.J. Estimation of Total Factor Productivity of Industrial Enterprises in China: 1999–2007. *China Econ. Q.* **2012**, *11*, 541–558. [CrossRef]