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Influencing Factors of Enterprise Intelligent Manufacturing Based on the Three Stages of Intelligent Manufacturing Ecosystems

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ABSTRACT

Intelligent manufacturing is an important method for transforming and upgrading enterprise intelligence. Studying the influencing factors of enterprises, intelligent manufacturing can help enterprises formulate more targeted intelligent manufacturing development strategies according to their own stage characteristics to accelerate the intelligent development. The concept of intelligent manufacturing ecosystem is proposed. By exploring the evolution process of intelligent manufacturing ecosystems, a three-stage theoretical model of influencing factors of intelligent manufacturing of enterprises is constructed. The theoretical model and related assumptions are verified using the empirical data of manufacturing enterprises of many provinces and cities in China. The results show that most factors in the digital stage, network stage, and intelligent stage significantly affect the development of enterprise intelligent manufacturing systems. This study provides theoretical reference and suggestions for manufacturing enterprises to develop intelligent manufacturing.

KEYWORDS

Ecological System, Hypothesis Testing, Influencing Factor, Intelligent Manufacturing, Questionnaire Method

INTRODUCTION

With the deep integration of information technology, manufacturing technology, and intelligent technology, as an advanced manufacturing process, intelligent manufacturing has become a novel path of intelligent transformation and upgradation of the global manufacturing industry. The level of intelligent manufacturing is regarded as an important indicator for measuring the core competitiveness of enterprises. The level of enterprise intelligent manufacturing is related to the stage of intelligent manufacturing development. The strategic objectives of different development stages have different requirements for the intelligent manufacturing level. Therefore, the main factors influencing enterprise

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intelligent manufacturing in different development stages must be explored, the degree of influence must be clarified, and an action path of different factors affecting the development of enterprise intelligent manufacturing needs to be developed. In addition, decision-making suggestions and reference for the development of enterprise intelligent manufacturing must be provided, which is important to improve the level of enterprise intelligent development and the national strategies for manufacturing power.

Recently, manufacturing industries of various countries have suggested national strategies and plans to improve the development of the traditional manufacturing industry using information technology, for example, "industry 4.0" in Germany, "national strategic plan for advanced manufacturing industry" in the United States, "industry 2050 strategy" in the United Kingdom, and "made in China 2025" in China. These strategic plans are advanced manufacturing development strategies with intelligent manufacturing technology as the core. Meanwhile, researchers are also paying close attention to the research and development of intelligent manufacturing in manufacturing enterprises. Wik et al. illustrated that the ability of manufacturing enterprises to develop intelligent factories is related to the production system, application field, and application technology of enterprises based on the intelligent factory solutions of South Korea and Sweden and their digital-related strategies (Wiktorsson et al., 2018). Zhou et al. showed that Chinese manufacturing enterprises can develop their own intelligent manufacturing capability upgrading path, according to their own capabilities and industry characteristics (Zhou et al., 2019). He et al. proposed a multi-scale integrated intelligent manufacturing model for the chemical industry and discussed the key technologies associated with the interconnected chemical industry (He et al., 2020). Ma et al. proposed a data-driven intelligent manufacturing framework based on the demand response of energy-intensive industries (Ma et al., 2020).

In terms of influencing factors of intelligent manufacturing, Su and Yang studied the influencing factors of intelligent transformation and the upgrading of manufacturing enterprises based on grounded theory (Su and Yang, 2018). Meng and Zhao focused on the factors that affect the development of traditional manufacturing to intelligent manufacturing (Meng and Zhao, 2018). Liu et al. found that external factors such as industrial chain factors, development factors, and capital factors have an important impact on enterprise intelligent manufacturing based on the SVR model (Liu et al., 2017). Based on knowledge acquisition and motivation, Stadnicka et al. studied human factors in an intelligent manufacturing system (Stadnicka et al., 2019). Oliff et al. proposed a human–computer interaction and collaboration framework for intelligent manufacturing that integrates human knowledge to study the relationship between robots and operators to better understand human impact on the production process (Oliff et al., 2018). Owusu A. explored the determinants of Cloud BI adoption among Ghanaian small-medium enterprises (Owusu, 2020).Yu et al. studied the impact of government subsidies on the intelligent transformation of new energy vehicle enterprises (Yu et al., 2020).

Although various researchers have explored the application of intelligent manufacturing in enterprises from multiple perspectives, not many quantitative studies have focused on the influencing factors of enterprise intelligent manufacturing, and a few of these have been integrated into a systematic comprehensive and comprehensive study. Moreover, no separate study has been conducted on the influencing factors of enterprise intelligent manufacturing from the perspective of enterprise development stage, and ignored the development of intelligent manufacturing in different periods.

Based on this, from the perspective of development, we systematically expound the main influencing factors of enterprise intelligent manufacturing in different stages, suggest the concept of intelligent manufacturing ecosystem based on the concept of ecosystems in biology, and discuss the evolution process of enterprise intelligent manufacturing ecosystems. Thus, by analyzing relevant literature and via in-depth investigation of enterprises, we built a factor model of factors influencing enterprise intelligent manufacturing in different stages. A three-stage factor model of enterprise intelligent manufacturing is constructed. The data for the study were collected in the form of a questionnaire. SPSS software was used to analyze the influencing factors of enterprise intelligent manufacturing to verify the main influencing factors and the mechanism of their effect on enterprise intelligent manufacturing. Further, a reliable theoretical basis is provided for promoting the intelligent process of manufacturing enterprises. We also provide a policy reference for the national development of intelligent manufacturing.

The rest of this paper is organized as follows. Section II discusses the evolution process of the intelligent manufacturing ecosystem. The evolution of intelligent manufacturing is presented in well-defined sub-sections. First, an analogy with a biological ecosystem is discussed. Then, the three stages of the evolution process are detailed along with their aims and limitations. Section III presents the three-stage model and its variables, and lists the assumptions for each stage. Section IV presents an empirical analysis of the influencing factors. Section V offers our conclusions and future research.

EVOLUTION PROCESS OF INTELLIGENT MANUFACTURING ECOSYSTEM

Concept of Intelligent Manufacturing Ecosystem

In-depth studies on intelligent manufacturing have revealed similarities between intelligent manufacturing and biological phenomena, and biological viewpoints have been adopted in intelligent manufacturing; thus, the concept of intelligent manufacturing ecosystems has been proposed. In the traditional sense, an ecosystem includes all living organisms and their living environment in a certain natural area (Jorge, 2007; Lv, 2019). The environment refers to the abiotic environment, including living conditions (such as water, temperature, and sunlight) and living space.

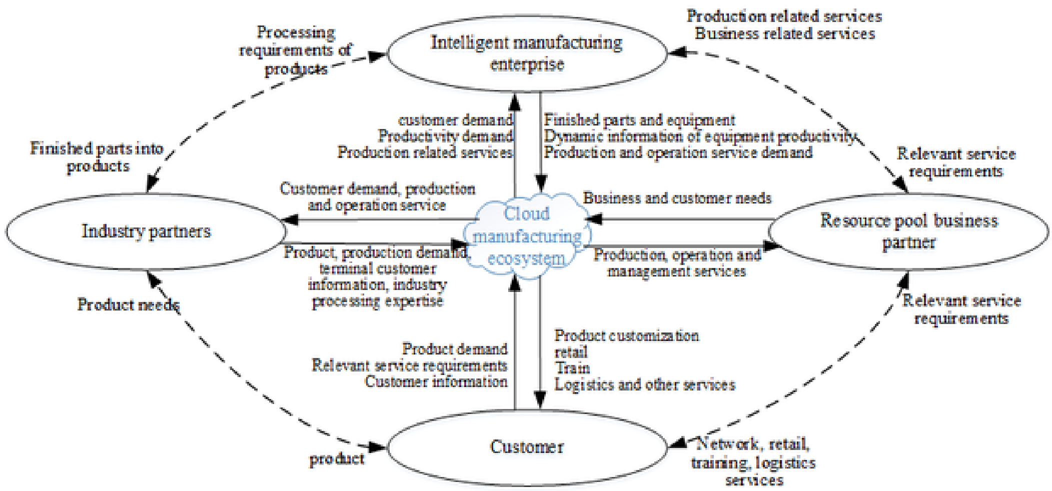
The evolution of the traditional ecosystem refers to the process of ecosystem succession caused by changes in the abiotic environment and due to biological evolution (Mao and Zhao, 1987). The change in the abiotic environment is an external cause, and it mainly includes natural and human factors. Biological evolution is an internal cause; it mainly refers to the interaction among producers, consumers, and translators. Under the influence of external and internal factors, according to Darwin's theory of biological evolution—survival of the fittest—finally, the ecosystem presents a relatively stable structure and state (Guo, 2011).

Similarly, under the influence of external (new round of information technology, national policies, etc.) and internal (enterprise transformation demand, production efficiency, etc.) factors, the manufacturing industry has to move forward to find a new and better manufacturing model. Based on this, in this study, an intelligent manufacturing ecosystem (Figure 1) is proposed to explore the main influencing factors of enterprises affecting the development process of intelligent manufacturing. The intelligent manufacturing ecosystem in this study refers to all enterprises and their intelligent environments in the manufacturing industry.

The evolution of intelligent manufacturing ecosystems refers to the development process of enterprise intelligent manufacturing caused by changes in the intelligent environment and enterprise development. The changes in the intelligent environment are an external factor, and they mainly include the hardware (intelligent equipment, network devices, sensing devices, etc.) and software (strategic organizations, human resources, intelligent technology, etc.) required for enterprise development. Enterprise development is an internal factor that mainly refers to the market demand among intelligent manufacturing enterprises, suppliers, and customers. The interaction of internal and external factors form an intelligent manufacturing ecosystem with mutual correlation, mutual influence, and integration development.

In the intelligent manufacturing ecosystem shown in Figure 1, the outer circle represents the intelligent environment with elements such as strategic organization, human resources, intelligent equipment, and intelligent technology. The inner circle represents the development among enterprises (Ying et al., 2018). In this circle, enterprises need, influence, and develop each other.

Figure 1. Intelligent manufacturing ecosystem



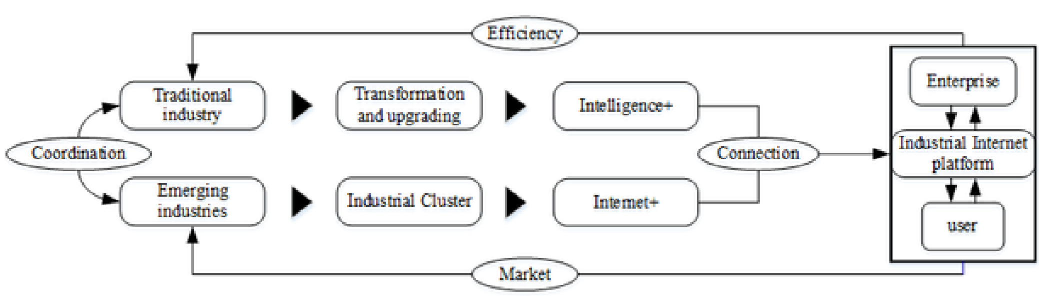
Evolutionary Process

In this study, we analyzed the iterative evolution process of an enterprise intelligent manufacturing ecosystem from the perspective of digital manufacturing to intelligent manufacturing, based on the development ability of each stage. The intelligent manufacturing ecosystem of the enterprise is divided into three stages: digital stage, networked stage, and intelligent stage. The following sections will elaborate on each of these stages and intensively analyze the characteristics and capabilities of enterprise intelligent manufacturing ecosystems to explore and explain the evolution process of an enterprise intelligent manufacturing ecosystem. The evolution process of an enterprise intelligent manufacturing ecosystem is shown in Figure 2.

Digital Stage

As the initial stage of an enterprise intelligent manufacturing ecosystem, the digital stage lays down a digital foundation for promoting the development of intelligent manufacturing. The main principle of this stage is as follows. 1. Talent building: To achieve a reserve of professional talents and accelerate the development of enterprise information, manufacturing fields, management, and other talents. 2. Formulate the development strategy of the enterprise in the digital stage. 3. Digitize equipment, spare parts, products, and processes; collect networked data collection of production equipment; and standardize data management (Lyly-Yrjanainen et al., 2016). 4. Develop system software (control

Figure 2. Evolution process of an enterprise intelligent manufacturing ecosystem



system, information system, management system, etc.) by applying each system to help enterprises achieve digital and transparent management.

Although digital manufacturing can effectively shorten the product development cycle, improve production efficiency and product quality, and reduce operating costs and resource and energy consumption, it is far from enough to realize the intelligent development of enterprises. With the implementation of enterprise digitalization, enterprise data resources need to be integrated, and an integration platform is necessary. Therefore, the manufacturing industry is promoting the iterative development of manufacturing ecosystems to the second stage in continuous exploration.

Networked Stage

The network stage is the semi-mature state of enterprise intelligent manufacturing, which is a sign of qualitative change in enterprise intelligent manufacturing. The main aim of this stage is as follows. 1. To realize product life cycle integration and open end-to-end data flow. 2. To achieve management and control integration, which is called vertical integration, from the decision-making level of the enterprise to the implementation level of the primary level. The enterprise realizes cross-equipment and cross-system data sharing, in which cross-equipment and cross-system refers to the integration of information between various equipment and systems (PDM, MES, ERP, etc.). This is done to realize data interconnection and interworking, to build a digital factory with integrated management and control platform as the core, and to connect all information islands within the enterprise. This can help realize coordination of all links in the entire manufacturing process (Weber, 2015). 3. To realize horizontal integration, that is, integration of production, supply, and marketing, and to build an industrial chain with a high level of collaboration. Thus, cross-enterprise data sharing and collaboration can be achieved between enterprises in the entire industrial chain, including data collaboration, resource collaboration, and process collaboration among enterprises, to optimize the allocation of resources (Lee and Jin, 2016).

With data technology driving the network stage, this stage is called "Internet + Manufacturing" mode, and the manufacturing capability of enterprises increases considerably. However, difficulties in sharing and innovation are not addressed. Therefore, the enterprise intelligent manufacturing ecosystem continues to develop into the third stage.

Intelligent Stage

The intelligent stage is the mature state of enterprise intelligent manufacturing. It involves iterative development based on the digital and network stages. It takes digital ability as the solid foundation and network ability as the middle-end force and fully integrates the new generation of artificial intelligence technology (Internet of Things technology, big data technology, cloud computing technology, etc.). The main aim of this stage is as follows. 1. Transformation from product-centered to user-centered: the enterprise product chain extends from products to services and provides more value-added services for users through the remote operation of products (Zhang et al., 2016). 2. Through deep learning, transfer learning, reinforcement learning, and other technologies, manufacturing data and information are automatically processed into knowledge using a cloud platform to realize intelligent analysis, prediction, and decision optimization. 3. To realize intelligent service and large-scale personalized customization of enterprises, enterprises can transform from production-centered manufacturing to service-centered manufacturing. The development of the manufacturing service industry can be promoted, and the innovation and service capacity of manufacturing enterprises can be significantly improved (Giret et al., 2016).

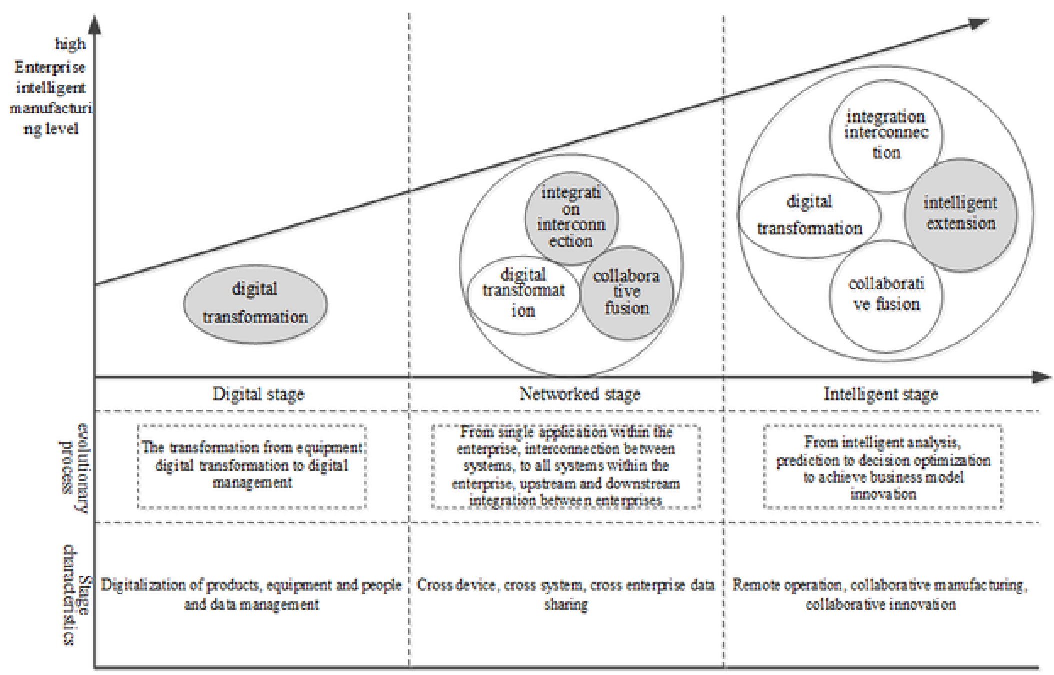
Through the analysis of the evolution process of the intelligent manufacturing ecosystem of enterprises, from the perspective of intelligent environment, the three stages of digitalization, networking, and intellectualization have their own characteristics and key problems to be solved. They also have an internal relationship with integrated development. Each development stage is based on the previous stage, and enterprise intelligent manufacturing can be achieved by gradually moving from one stage to the next. This study focuses on the characteristics of the three stages and the main factors influencing stage development. The characteristics of enterprise intelligent manufacturing in different development stages are shown in Figure 3. In the digital stage, enterprises mainly perform digital transformation, build digital chemical plants, perform digital transformation of equipment, and carry out multi-dimensional and full digital management. In the network stage, enterprises use network means to connect each ecological contact point, establish industrial Internet, and realize end-to-end automatic data flow. In the intelligent stage, enterprises improve the platform service support system of intelligent manufacturing ecosystems, use big data to explore potential value, and realize business model innovation.

INFLUENCING FACTORS AND THEORETICAL MODELS

The development of intelligent manufacturing from traditional manufacturing is affected by many factors, which are different in different stages. Many enterprises cannot implement intelligent manufacturing successfully because they do not adjust their development strategy in time according to their development stage and always choose the initial development strategy too rigidly. Therefore, it is very important to distinguish the main influencing factors of different development stages according to the characteristics of each period. In this study, the main influencing factors in the three-stage development process of enterprise intelligent manufacturing are studied, and the main influencing factors in different development stages of enterprise intelligent manufacturing are suggested as theoretical assumptions.

According to the evolution process of the three stages mentioned in section B, the main influencing factors of the digital stage are digital equipment, digital information system, information talents, strategic organization, network environment, and security. The main influencing factors in the network stage are system integration, equipment interconnection, system security, and collaborative

Figure 3. Characteristics of enterprise intelligent manufacturing in different development stages



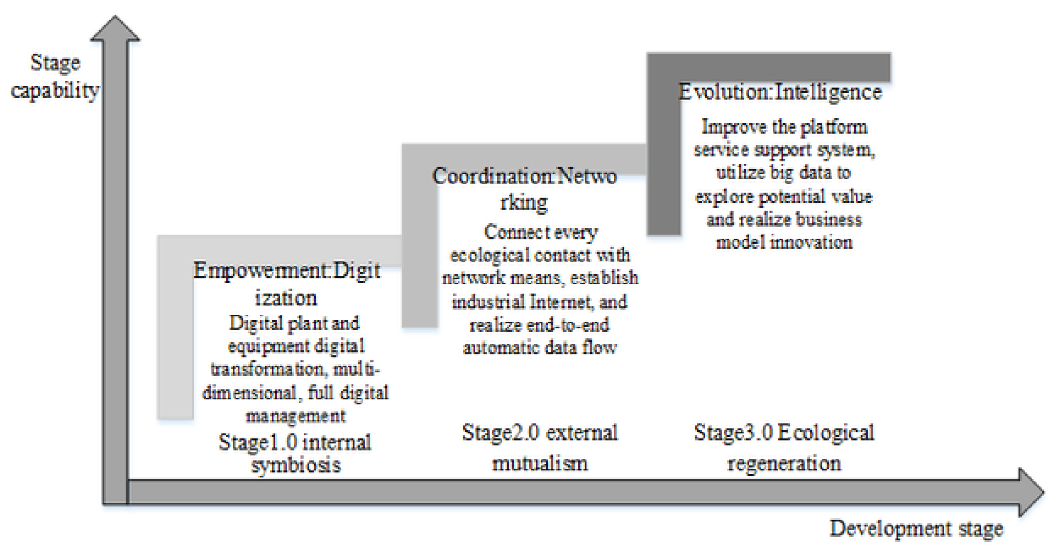
integration among enterprises. The main influencing factors in the intelligent stage are remote operation, personalized customization, and intelligent service. The main influencing factors model in the three stages of the development of enterprise intelligent manufacturing are shown in Figure 4.

(1) Digital transformation. Digital transformation is the basis of intelligent manufacturing. Digital equipment, digital information system, information talents, strategic organization, and network environment and security are the basic elements required to realize digital transformation. Among them, digital equipment is an important tool for workshop production, and it is the basis for digital workshop construction. Digital information systems change the ways of traditional manufacturing by integrating production jobs and equipment into the information system, to realize efficient and high quality production with an orderly flow of data. All intelligent equipment, intelligent management, and intelligent decision-making are based on human will. People are the application leaders of any software or hardware system, and their skills are further developed throughout the intelligent manufacturing process; therefore, it is of great significance to build information-based talents. Strategic organization implies that the development of intelligent manufacturing in an enterprise is always in line with the development strategy of the enterprise through strategic formulation, scheme planning and implementation, capital investment and use, and organization optimization and adjustment. Network environment and security refers to the use of fieldbus, industrial Ethernet, wireless network, Internet of Things, and other technologies to realize the interconnection and communication between devices and systems, and at the same time, detect and manage the availability, integrity, and confidentiality of users and equipment connected to the network.

Based on the main influencing factors of the digital stage, we have the following assumptions:

H_1: *Digital equipment has a positive impact on digital transformation.*
H_2: *Digital information system has a positive impact on digital transformation.*
H_3: *Information talents have a positive impact on digital transformation.*
H_4: *Strategic organization has a positive impact on digital transformation.*

Figure 4. Factors influencing the three stages of enterprise intelligent manufacturing capacity development



H_5: Network environment and security have a positive impact on digital transformation.

(2) Integration interconnection and collaborative integration. Integrated interconnection includes system integration and equipment interconnection. System integration refers to the interconnection and interoperability of various businesses and information in an enterprise, which achieves a state of complete integration of physical information. Through equipment interconnection, the digital equipment can realize network connection, remote data collection, centralized program management, big data analysis, etc. Collaborative fusion refers to the realization of collaborative integration among enterprises on the basis of digital transformation and integrated interconnection, to ensure system security. System security refers to monitoring, managing, and evaluating the information security of industrial control systems. Collaborative integration among enterprises refers to the collaborative optimization of various links among the enterprises.

Based on the main influencing factors of the network stage, we have the following assumptions:

H_6: System integration has a positive impact on the network integration interconnection.
H_7: Device interconnection has a positive impact on network integrated interconnection.
H_8: System security has a positive impact on network integration and interconnection.
H_9: Collaborative fusion among enterprises has a positive impact on networked collaborative fusion.
H_{10}: Digital transformation has a positive impact on integration, interconnection, and collaborative integration in the network stage.
H_{11}: Digital transformation has a positive impact on the intelligent manufacturing capacity of enterprises.
H_{12}: Integration interconnection and collaboration fusion in the network stage have a positive impact on the enterprise's intelligent manufacturing capability.

(3) Intelligent extension. Intelligent extension refers to the establishment of intelligent modes such as remote operation and maintenance, personalized customization, and intelligent service. Remote operation and maintenance implies that intelligent equipment and intelligent products have the functions of data collection, communication, and remote control, and they can carry out remote monitoring, fault warning, and operation optimization through the network and platform, which are an innovative service provided by manufacturing enterprises. Personalized customization is to introduce users into the production process in advance. Personalized requirements can be realized through differentiated customization parameters and flexible production. Intelligent service is to bring better experience and more value-added services for customers by means of information technology.

Based on the main influencing factors of the intelligent stage, we have the following assumptions:

H_{13}: Remote operation has a positive impact on intelligent extension.
H_{14}: Personalized customization has a positive impact on intelligent extension.
H_{15}: Intelligent service has a positive impact on intelligent extension.
H_{16}: The integration interconnection and collaboration fusion in the network stage have a positive impact on intelligent extension.
H_{17}: The intelligent extension of the intelligent stage has a positive impact on the enterprise's intelligent manufacturing capability.

In summary, the proposed three-stage model has 16 variables and 17 path relationships, as shown in Figure 5. Each path relationship has an assumption. To verify the hypothesis of the influencing factors, we designed a questionnaire on the influencing factors in the development stage of enterprise intelligent manufacturing. The data collected through questionnaires were processed and analyzed using the structural equation model method, SPSS, Amos, and other software. Finally, the results of hypothesis verification were analyzed.

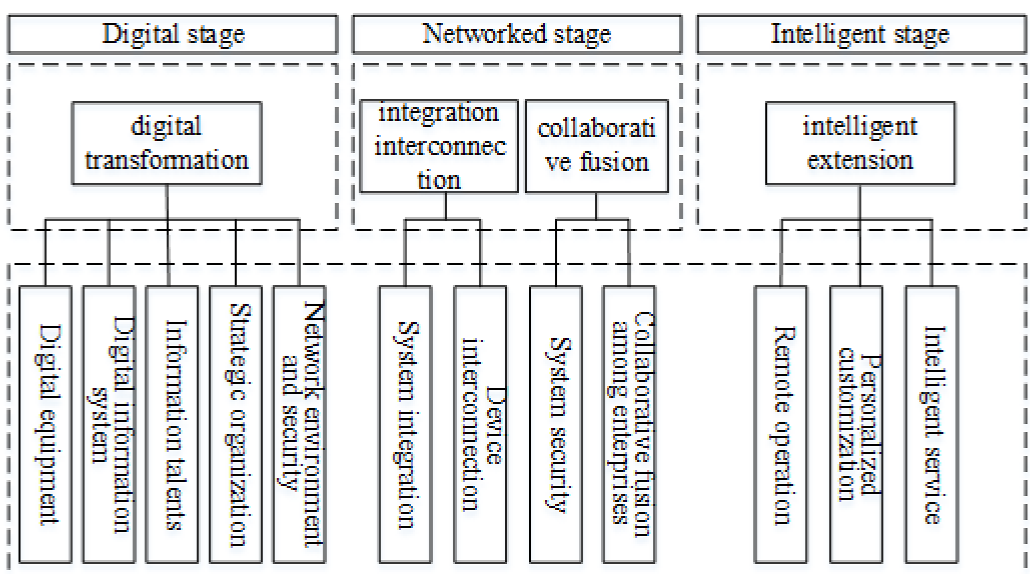
EMPIRICAL ANALYSIS

China features a large manufacturing sector, comprising various manufacturing enterprises. Each of these enterprises has a different development status; some of them are leading enterprises with intelligent manufacturing and perfect digital level and network ability, whereas some are small enterprises that have recently implemented digital transformation. Therefore, in view of the overall development of intelligent manufacturing in Chinese manufacturing enterprises, this study proposes a three-stage analysis of the influencing factors of intelligent manufacturing in manufacturing enterprises in order to explore the primary influencing factors in different stages of intelligent manufacturing development; thus, this study is expected to help manufacturing enterprises formulate and implement strategic decisions according to their own stages and to accelerate the completion of the intelligent transformation of manufacturing enterprises.

Questionnaire Design

First, a questionnaire was designed according to the three-stage influencing factors in the constructed influencing factor model. Second, a typical manufacturing enterprise was selected, and in-depth interviews were conducted with its information department manager, production department manager, and technical governors in order to seek expert opinions on improving the rationality and sufficiency of item setting to complete the design of the questionnaire. In the questionnaire, each question was based on a 5-level Likert scale, according to which the influence degree of factor variables can be 5, 4, 3, 2, or 1, which correspond to very influential, comparatively influential, generally influential,

Figure 5. Three-stage theoretical model of influencing factors for the development of enterprise intelligent manufacturing capacity



not influential, and completely uninfluential, respectively. Individuals attempting the questionnaire assign scores according to their actual cognition. The variables of the influencing factors are shown in Table 1. To ensure the scientific nature and validity of the questionnaire, a dry run of the questionnaire was conducted, and the questionnaire was improved according to feedback obtained during pre-distribution. Finally, the questionnaire was sent out in the form of a two-dimensional code through Questionnaire Star APP.

Data Collection

To ensure efficiency when collecting responses for the questionnaire, selected sample enterprises were contacted via telephone to inquire whether they were willing to be the object of the survey. Subsequently, electronic questionnaires were sent to the enterprises willing to fill in the questionnaire, and information regarding their department managers, production department managers, and technical governors was obtained in order to organize the personnel from each department of the enterprise and to fill in the questionnaires. Questionnaires were sent to 32 enterprises in 13 provinces and cities (Anhui, Shanghai, Zhejiang, Tianjin, Beijing, Jiangsu, Shandong, Guangdong, Sichuan, Hunan, Henan, Ningxia, and Hubei) in China. A total of 242 questionnaires were collected, 15 of which were invalid (the responses were not serious and several items had been skipped); thus, 227 valid questionnaires were obtained.

Data Analysis and Hypothesis Testing

Descriptive Analysis

A total of 227 valid samples were obtained from this questionnaire survey, and the overall sample distribution is shown in Table 2.

Data Reliability and Validity Analysis

Reliability analysis assesses the consistency and stability of the scale. Currently, the most widely used evaluation index is Cronbach's alpha, developed for the Likert scale (1951). It refers to the average value of the half confidence coefficient obtained by all possible item division methods of the scale; if a scale has n questions and the average correlation coefficient among them is given by r, the standardized coefficient of the scale is $\pm = nr / [(n-1)r + 1]$. When the correlation between the measurement indexes is improved, the reliability of the scale also increases. Generally, Nunnally's criterion is that Cronbach's alpha reaches 0.7. However, in basic research and applied research, a reliability of 0.8 is preferred (Park et al., 2015).

Validity analysis assesses the validity of the scale (Li and Han, 2019). In general, before factor analysis, a suitability test of Kaiser Meyer Olkin sampling and Bartlett's Test of sphericity should be performed. According to Kaiser, when the KMO value is less than 0.5, the structure effect is poor; when the KMO value is between 0.6 and 0.7, the structure validity is acceptable; and when the KMO value is between 0.7 and 0.8, the structure validity is good. When the KMO value is greater than 0.8, the structure validity is very good.

In this study, 227 valid questionnaires were collected from Questionnaire Star APP. SPSS22.0 was used to analyze the reliability of the questionnaire, and the Cronbach's alpha value of each latent variable and the overall questionnaire was obtained, as shown in Table 3. In Table 3, the Cronbach's alpha value of each latent variable is greater than 0.7, and the overall Cronbach's alpha value of the questionnaire is 0.926, indicating that the questionnaire designed in this study has high reliability and meets the requirements. The values obtained by the Kmo test and Bartlett's sphericity test were also within a reasonable range, and the structure validity of the questionnaire was good, as shown in Table 4.

Table 1. Variables of influencing factors

Variable name	Variable description
Digital equipment	Carry out digital transformation of equipment and realize daily management of equipment using information technology (DE1) Realize state management of equipment using information technology (DE2)
Digital information system	Develop a production management and enterprise management system (such as ERP and BI) software (DS1) Daily work can be completed online through the information system (DS2)
Information talents	Increase the introduction of professional talent in automation, robot application, and intelligent manufacturing (IT1) Skill acquisition and promotion of existing employees (IT2)
Strategic organization	The organization has a vision to develop intelligent manufacturing and obtain capital investment (SO1) The organization has formed a strategic plan for the development of intelligent manufacturing and obtained a clear fund management system (SO2)
Network environment and security	Realize interconnection and communication between equipment and systems using field buses, industrial Ethernet, wireless networks, Internet of Things and other technologies (NS1) Network key equipment has security functions such as intrusion detection, user identification, access control, and integrity detection (NS2)
System integration	Interoperability among different systems such as production, resource scheduling, supply chain, R&D, and design (SI1) Information integration between digital information systems (SI2)
Equipment interconnection	Interconnection and information collection and transmission among production equipment (EI1) Entire life cycle of the product can be managed through digital transformation of equipment (EI2)
System security	Establish safety management requirements, event management, and corresponding systems for industrial public service systems (SS1) Regular safety risk assessments of major systems (SS2) Realize active defense and vulnerability scanning security protection for industrial control system security (SS3)
Collaborative integration among enterprises	Interconnection between upstream and downstream enterprises to achieve collaborative integration of production and operation (CI1)
Remote operation	Intelligent devices and products have the functions of data acquisition, communication, and remote control (RO1) Remote monitoring, fault warning, and operation optimization through network and platform (RO2)
Personalized customization	Realize a connection with the user's personalized needs through a personalized customization platform (PC1) Using industrial cloud and big data technology to mine and analyze user's personalized demand characteristics (PC2)
Intelligent service	Establish a standard product service system and conduct product service management through information systems (IS1) Realize online maintenance, intelligent scheduling, and innovative application services through the cloud platform (IS2)

Theoretical model test

AMOS24.0 was used to test the theoretical model and hypothesis using a structural equation model (Wu, 2016). Parameters such as χ^2/df, CFI, $RMSEA$, IFI, $PNFI$, $PGFI$, and TLI were selected as the evaluation indexes for the fitting degree of the data and model (Lee et al., 2019). In general, when $\chi^2/\mathrm{df} \le 3$, $CFI \ge 0.9$, $RMSEA \le 0.05$, $IFI \ge 0.9$, $PNFI \ge 0.5$, $PGFI \ge 0.5$, or $TLI \ge 0.9$, the model is considered to have a good fit and the theoretical model is deemed acceptable (Yu et al., 2019). As

Table 2. Sample distribution characteristics

Statistical characteristics	Category	Number of samples	Constituent ratio (%)
Industry type	Electronic appliances Biological medicine Automobile manufacturing Other	30 8 155 34	13.21 3.52 68.3 14.97
Manufacturing mode	Discrete type Flow type Other	74 123 30	32.60 54.18 13.22
Enterprise scale	1–300 people 300–1000 people 1000–2000 people More than 2000	44 23 41 119	19.38 10.13 18.06 52.43
Development stage of intelligent manufacturing	Digital stage Networked stage Intelligent stage	136 71 20	59.91 31.28 8.81

Table 3. Reliability of latent variables

Latent variable	Number of observation variables	Cronbach's alpha
Digital equipment (DE)	2	0.874
Digital information system (DS)	2	0.752
Information talent (IT)	2	0.779
Strategic organization (SO)	2	0.881
Network environment and security (NS)	2	0.701
System integration (SI)	2	0.897
Equipment interconnection (EI)	2	0.822
System security (SS)	3	0.921
Collaborative integration among enterprises (CI)	1	0.886
Remote operation (RO)	2	0.842
Personalized customization (PC)	2	0.913
Intelligent service (IS)	2	0.845
Population	24	0.926

Table 4. KMO test and Bartlett's sphericity test

KMO sampling suitability quantity		0.913
Bartlett' sphericity test	Approximate chi square	11203.719
	Freedom	613

shown in Table 5, the values of Ç^{2} / df , *CFI* , *RMSEA* , *IFI* , *PNFI* , *PGFI* , and *TLI* are within a reasonable range, indicating that the model has good structural validity.

Through analyses of the P value, we can determine whether the original hypothesis passed the test. Generally, the P value is less than 0.05, and a P value less than 0.01 is considered very significant. Therefore, the significance level was set at 0.05. The theoretical model hypothesis test results are shown in Table 6.

Table 5. model fitting index results

Ç^{2} / df	*CFI*	*RMSEA*	*IFI*	*PNFI*	*PGFI*	*TLI*
1.745	0.923	0.046	0.937	0.641	0.677	0.936

Table 6. hypothesis test results of the theoretical model

Serial number	Path	Path coefficient	P value	Test results
1	Digital transformation ¬ Digital equipment	0.242	0.002	Significant
2	Digital transformation ¬ Digital information system	0.196	0.019	Significant
3	Digital transformation ¬ Information talents	0.375	***	Very significant
4	Digital transformation ¬ Strategic organization	0.168	0.031	Significant
5	Digital transformation ¬ Network environment and security	0.017	0.734	Not significant
6	Network integration interconnection ¬ System integration	0.228	0.01	Significant
7	Network integration interconnection ¬ Equipment interconnection	0.174	0.029	Significant
8	Network integration interconnection ¬ System security	0.181	0.025	Significant
9	Networked collaborative fusion ¬ Collaborative fusion among enterprises	0.013	0.782	Not significant
10	Integration, interconnection, and collaborative integration in the network stage¬ Digital transformation	0.169	0.03	Significant
11	Intelligent manufacturing capacity of enterprises ¬ Digital transformation	0.339	***	Very significant
12	Intelligent manufacturing capacity of enterprises ¬ Integration, interconnection, and collaborative integration in the network stage	0.247	0.001	Significant
13	Intelligent extension ¬ Remote operation	0.536	***	Very significant
14	Intelligent extension ¬ Personalized customization	0.268	***	Very significant
15	Intelligent extension ¬ Intelligent service	0.219	0.016	Significant
16	Intelligent extension ¬ Integration, interconnection, and collaborative integration in the network stage	0.184	0.023	Significant
17	Intelligent manufacturing capacity of enterprises ¬ The intelligent extension of the intelligent stage	0.290	***	Very significant

Note: *** indicates a P value < 0.001.

Inspection Results and Discussion

The hypothesis test results in Table 6 show that the P values of digital equipment, digital information system, information talents, and strategic organizations for digital transformation are all less than 0.05, which indicates that these four factors have a positive impact on digital transformation; thus, hypotheses H1, H2, H3, and H4 are verified. However, the P values of the network environment and security for digital transformation are greater than 0.05, which indicates that the impact of network environment and security on digital transformation is not significant; thus, hypothesis H5 is not verified. The P values of system integration, equipment interconnection, and system security to the network integration interconnection are all less than 0.05, which indicates that these three factors have a positive impact on network integration interconnection. Thus, hypotheses H6, H7, and H8 are verified. However, the P value of inter-enterprise collaboration fusion to networked collaboration fusion is greater than 0.05, which indicates that the impact of inter-enterprise collaboration fusion on networked collaboration fusion is not significant; hence, hypothesis H9 is not verified. The P values of digital transformation for integration, interconnection, collaboration, and enterprise intelligent manufacturing capacity in the network stage are all less than 0.05; thus, hypotheses H10, H11, and H12 are verified. Furthermore, the P values of remote operation, personalized customization, and intelligent service to intelligent extension are all less than 0.05, which indicates that these three factors have a positive impact on intelligent extension; therefore, hypotheses H13, H14, and H15 are verified. The P value of integration interconnection and collaboration fusion in the stage of network to intelligent extension, and intelligent extension in the stage of intelligence to an enterprise's intelligent manufacturing capacity are all less than 0.05; thus, hypotheses H16 and H17 are verified.

The hypothesis test results not only prove that the hypothesis proposed in this study is valid but also show that the influencing factors of each stage have a positive impact on the development of each stage and the development of enterprise intelligent manufacturing. For example, digital equipment, digital information systems, information talents, and strategic organization factors have an important impact on the digital stage of enterprise intelligent manufacturing. The digital transformation of the digital stage also has a positive impact on the networked stage and the enterprise's intelligent manufacturing capacity, which reflects the importance of the digital stage as the basic stage of the enterprise's intelligent manufacturing development. System integration, equipment interconnection, and system security factors have an important impact on the networked stage of enterprise intelligent manufacturing. The integration, interconnection, and collaborative integration of the networked stage also positively affect the intelligent stage and the enterprise's intelligent manufacturing capacity, which reflects the evolution of the enterprise's intelligent manufacturing development. Remote operation, personalized customization, and intelligent service have an important impact on the intelligent stage of enterprise intelligent manufacturing. The intelligent extension of the intelligent stage also has a positive impact on the enterprise's intelligent manufacturing capacity, thus reflecting the qualitative improvement and breakthrough in the development of the enterprise's intelligent manufacturing. Enterprises should solve their own problems and difficulties in intelligent manufacturing development according to their actual development stage of intelligent manufacturing and the influencing factors of stages and must effectively promote the intelligent transformation of enterprises.

Based on the above mentioned theoretical analysis and practical verification results, combined with actual scenarios of the enterprise, this study shows that the level of intelligent manufacturing in enterprises can be improved in terms of the following aspects:

(1) Manufacturing enterprises in the digital stage should focus on digital transformation. The intelligent manufacturing system of enterprises at this stage is not perfect; the basic support capacity is insufficient, the industrial Internet infrastructure needs to be improved, and problems such as insufficient information security awareness and inadequate protection exist. In this study, the hypothesis test results of the theoretical model show that the network environment and security

do not have a significant impact on digital transformation. However, when vigorously developing intelligent manufacturing, network environment and security are considerably important; only under the premise of ensuring data security and system security can information security risks be minimized. This result is likely due to the fact that the interviewed enterprises and their employees neglected the information security risks of digital transformation. Therefore, manufacturing enterprises should establish a timely framework for the protection of network environment and security, form an information security management system, and effectively reduce the potential risk of information security caused by data sharing in the context of intelligent manufacturing. Moreover, enterprises should implement a solid foundation to ensure the smooth development of intelligent manufacturing.

(2) For manufacturing enterprises in the network stage, integration, interconnection, and collaborative integration should be enhanced. Enterprises at this stage have a certain digital foundation; thus, they should implement network collaborative manufacturing and build a networked manufacturing resource collaboration platform and industrial big data service platform to realize interactive sharing of information and data resources inside and outside the enterprise. In this study, the theoretical model hypothesis test results show that collaborative integration between enterprises does not have a significant impact on network collaborative integration. However, the upstream and downstream manufacturing links among enterprises should realize parallel organization and collaborative optimization. Therefore, manufacturing enterprises should strengthen the cooperation and integration among enterprises. Additionally, enterprises should integrate different business application systems effectively through a unified platform, real-time database, and other technologies to realize complete sharing of data.

(3) For manufacturing enterprises in the intelligent stage, it is necessary to strengthen intelligent extension. At this stage, enterprises have certain digital and network capabilities. Thus, enterprises should actively perform large-scale personalized customization, remote operation and maintenance services as well as implement new manufacturing modes to help manufacturing enterprises transform into service-oriented ones.

CONCLUSION AND FUTURE RESEARCH

This study proposes the concept of an intelligent manufacturing ecosystem and analyzes the evolution process of an enterprise intelligent manufacturing ecosystem. According to the evolution characteristics of enterprise intelligent manufacturing at different development stages, the main influencing factors were analyzed, and a three-stage theoretical model of the influencing factors of intelligent manufacturing in enterprises was constructed. In addition, hypotheses of the relationships among the influencing factors in the theoretical model are proposed. A questionnaire survey and the SPSS software were used to collect and process data, and relevant hypotheses were verified by constructing a structural equation model to obtain the main influencing factors of manufacturing enterprises at different development stages. The main influencing factors of the digital stage are digital equipment, digital information systems, information talents, and strategic organization; those of the networked stage are system integration, equipment interconnection, and system security; and those of the intelligent stage are remote operation, personalized customization, and intelligent service.

By analyzing these main influencing factors of intelligent manufacturing at different stages, this study is expected to help enterprises combine their own development status to formulate more targeted development strategies of intelligent manufacturing and improve the level of intelligent manufacturing. Additionally, the study also provides theoretical guidance for the intelligent transformation and upgradation of relevant manufacturing enterprises.

However, this study involves a few limitations. First, the number of questionnaire survey samples was small. Thus, future studies should increase the number of questionnaires in order to collect a large amount of sample data. Second, the questionnaire used in this study involved a few abstract concepts, which may hinder the questionnaire from achieving the expected effect. In the future, we intend to focus on using the influence factors of intelligent manufacturing to develop an evaluation index, explore the development status of enterprise intelligent manufacturing, and evaluate the level of enterprise intelligent manufacturing.

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