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Research on digital transformation of China´s traditional manufacturing industry enabled by digital economy based on system dynamics

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ABSTRACT

The digital transformation of traditional manufacturing industry is an inevitable trend and inherent development requirement of China's digital economy. This paper systematically researches the digital transformation mechanism of traditional manufacturing industry enabled by digital economy from the social, technical, innovative environmental and organizational sub-systems based on the system dynamics (SD) and the social shaping of technology theory (SST). The simulated experiments predicate the different digital transformation paths of the labor-intensive, capital-intensive and technology-intensive traditional manufacturing enterprises under the guidance of Industry 4.0 or "Industry of the future" policy by constructing the system dynamics model of causality, stock flow process, which has vital significance for China's manufacturing industry to transform from a giant towards a manufacturing power.

KEYWORDS

Traditional manufacturing industry; Digital transformation; Digital economy; The theory of the social shaping of technology; System dynamics

1 Introduction

Digital transformation is the innovation process from the multiple levels of the individual, organization and industry supported by the infrastructure of digital technology, digital product and digital platform. It has impacted the development path of traditional manufacturing industry, organizational model and national strategy (Banalieva & Dhanaraj, 2019). With the new round of industrial competition in the global economy and the strategy of "Made in China 2025", the digital technologies of IoT, AI and Industry 4.0 have become the new driving forces for the digital transformation of the traditional manufacturing industry (Guo, 2019). In the process of digital transformation, China's traditional manufacturing industry needs to change previous value creation mode, seek cross-boundary partners from a larger value network, and shift their focus from their own interests to the value maximization of the entire network (Choudhary et al., 2019), which can overcome the double resistances of manufacturing reflux in the developed countries and the rapid development of manufacturing in emerging economies (Zhang & Cai, 2015).

The digital economy reconstructs the value creation logic of enterprises, so that the way of

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value creation of enterprises is no longer limited to a single enterprise, but is co-created with more subjects, which in turn brings a series of positive effects for the enterprise's digital transformation (Lichtenthaler, 2020). Specifically, it mainly involves two aspects: one is to accelerate the innovation integration process of user experience, integration of digital and physical modules, and industrial integration through digital technology (Henfridsson et al., 2018); the other is to improve the market position and influence of the enterprise by re-factoring the basic producing ability of IE, cultivating the lean management innovation power, optimizing the industrial structure (Huang & Qi, 2015). Digital transformation is a process that starts from the infrastructure of digital technology, digital products and digital platform, and then leads to changes in individual, organizational, industrial and other levels (Zeng et al., 2021). The digital transformation of the traditional manufacturing industry needs to reform the enterprise structure and work process at all levels (industries, organizations, individuals, etc.), rather than make simple construction efforts from the technological layer alone (Gregory, 2019). Therefore, the digital transformation of the traditional manufacturing industry, as a dynamic, open and complex system including the political, social organizational, cultural factors and so on. However, there are few research on how to promote the digital transformation of traditional manufacturing enterprises from the systematic prospects of social, economic factors as well as technical considerations.

With the rapid application of IoT and Industry 4.0 technologies, the digital transformation of the traditional manufacturing industry has become an important way of spurring economic growth, giving priority to the integration of digital economy with manufacturing industry. This paper researches the dynamic mechanism of digital transformation for China's traditional manufacturing industry based on the theory of the social shaping of technology (SST), which has developed as a response to techno- economically rational and linear conceptions of technology development and its consequences (Robin & David, 1996). The SST theory emphasizes the mutual connections between technology and society, avoids the unilateralism and extremity in technological determinism and social determinism, so it is closer to the external instance between technology and society (Sheng, 2007). In order to investigate the digital development ways of traditional manufacturing industry, this paper constructs the system dynamics model by Vensim software to simulate the traditional manufacturing industry to reconstruct the digital value chain, digital supply chain and industrial ecological chain by the digital technologies of IoT, Industry 4.0 under the guidance of innovation policies. System dynamics (SD) is an applied discipline that makes a systematic analysis of social and economic problems by combining qualitative and quantitative methods, studies quantitatively the dynamic behavior of system development on the basis of system feedback control theory and by means of computer simulation (Richardson, 2001; Saleh et al., 2010). The research methods and simulation results of this paper has vital significance for China's manufacturing to achieve high-quality development in policy guidance, market environment and enterprise decision-making.

2 Digital transformation dynamic model of traditional manufacturing based on SST

From the social perspective, the state of manufacturing is constantly changing due to volatility in global, economic, and policy landscapes. Not to mention, many manufacturing businesses were severely hit by the pandemic and needed to adapt quickly to stay afloat.

Therefore, this entails a broad range of relevant actors from the state, associations and civil society, to develop the digital literacy, digital density and digital social welfare in the era of digital economy. From the digital technology perspective, greater network capabilities of 5G, the push of IoT, Industry 4.0, machine learning, and data-driven predictive analytics all leave a mark on manufacturing, which adapts quickly to changes in the customer demands and market to secure competitive advantage. From the traditional manufacturing perspective, the activities such as customer requirement expression, product design, production engineering, production services and production maintenance can be predicted by utilizing software tools, which make sure the products are customizable in the customer-centric value creation process. Digital collaboration of worldwide value chain networks is an indispensable part of enterprises' business model innovation. The digital technology can accelerate the innovation integration process, thus realizing integration of user experience, integration of digital and physical modules, industrial integration (Henfridsson et al., 2018). Figure 1 shows the digital transformation dynamic model of traditional manufacturing industry.

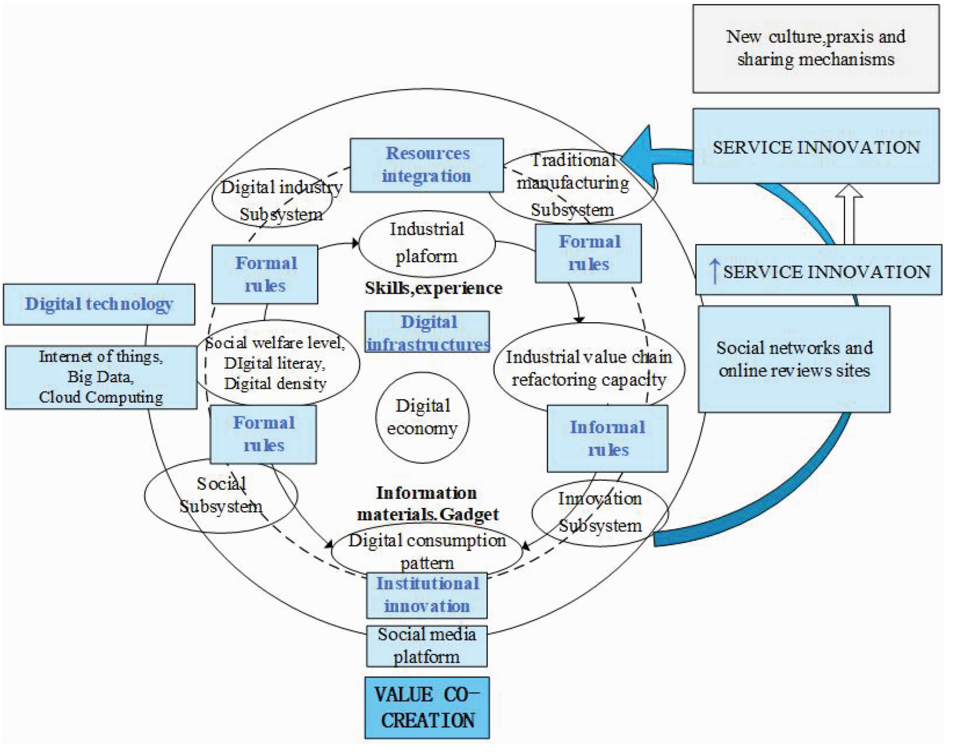


Figure 1 Digitalization transformation dynamic model of manufacturing industry based on SST

3 System dynamic model for digital transformation of traditional manufacturing

3.1 Construction and Analysis of Causality Diagram

A causality diagram is a qualitative description of the internal structure of the system and the basis of system dynamics modeling. This paper analyses the causal feedback relationship and constructs the causal diagrams for the digital transformation of traditional manufacturing from the digital society, digital industry, technology innovation and manufacturing industry sub-systems.

(1) Causal Analysis on digital society development sub-system

According to the 47th statistical report on internet development in China, the Internet penetration rate in China reached 70.4 percent by December 2020. The popularity of the Internet has expanded the scale of Internet users, which is conducive to promoting the upgrading of innovation in consumption patterns. Changes in consumption patterns are also promoting institutional innovation, which is conducive to the emergence of new forms of business. For example, the increasing size of Internet users year by year promotes the development and upgrading of online sales, thus the emergence of Alibaba, JD, and other excellent digital native enterprises. These companies are built on digital technologies such as cloud computing, and big data enable enterprises to dig deeper into user needs, so their growth will undoubtedly promote the development of digital technology, and the active social shaping of this process requires a broad digital social basis. Bojnec and Ferto (2009) investigated the impact of the Internet users number on the bilateral manufacturing export growth among OECD countries based on the gravity model using panel and cross-section regressions, and the empirical results suggest that the Internet stimulates manufacturing export. Mun and Chun (2015) investigated the effects of internet use on labor productivity, sales, and employment growth at the firm level in Korea, which the positive effects of internet use on the growth rates of labor productivity and sales are much more significant for manufacturing firms than service sector firms.

With the digital society development, the driving force of digital technology will gradually manifest itself, such as more students willing to study digital technology for high salaries and prospects. This will greatly improve the digital literacy of practitioners, thus driving employment growth, reducing labor costs, promoting regional development, and improving the urbanization level. These emerging services are summarized as wisdom and people's livelihood level, so as to measure the impact of social development on people's living standards. The causal diagram of the digital society development subsystem is shown in Figure 2, which consists of these 12 main variables of Internet penetration rate, digital density index, innovation of consumption pattern (Yang, 2008), wisdom and people's livelihood level, national happiness index, driving force of digital technology, digital literacy proficiency, urbanization level, social welfare level (Yang & Song, 2012), regional development level (Zhang et al., 2006), new urban jobs and labor cost.

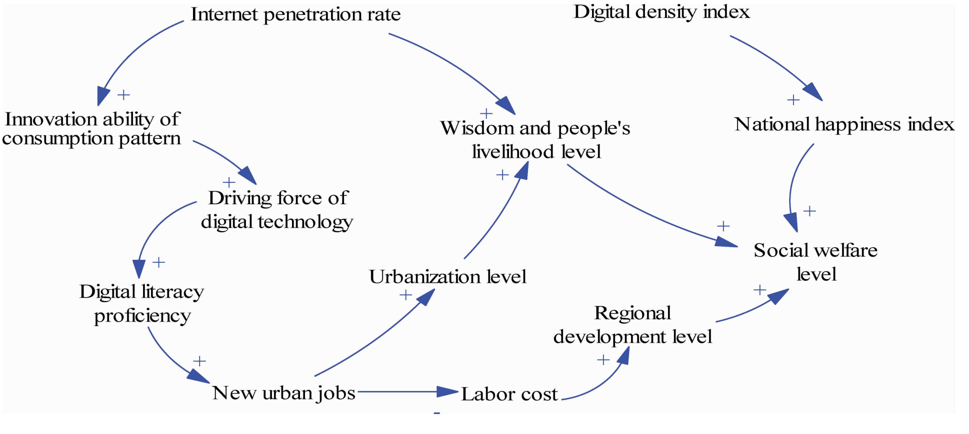


Figure 2 The causal loop diagram of the digital society development subsystem

(2) Causal Analysis on digital collaborative innovation subsystem

Existing economic theories focus on the concept of finished products. In the digital era, products gradually show characteristics of adaptive innovation. The data-driven product adaptive innovation not only forms a new business model with the adaptive feature of production and consumption, but also helps to promote the industrial system of digital innovation and promote the development of a digital economy (Xiao et al., 2020). China's traditional manufacturing industries have more opportunities for the digital technological innovation R&D and innovation systems based on product's adaptive characteristics and adaptive innovation. The complementarity of technology and innovation presents both coordination and market design challenges for innovators, often leading to market failure in the form of an excess of social gains over private returns. Constantly iterating digital technology and emerging digital resources will be a huge boost to improve the ability of innovation resource allocation based on the interactive information structure of instant feedback. The improvement of innovation resource allocation ability, iterative innovation ability and innovation system construction will enhance innovation efficiency and help promote the digital transformation of traditional manufacturing industry.

The digital collaborative innovation subsystem consists of 14 main variables: Driving force of digital technology, development level of traditional manufacturing industry, collaborative innovation competence (Liao & Yang, 2021), industry digital innovation ability (Teece, 2018), institutional innovation ability (Qiu, 2001), innovate resource allocation capabilities, Sci-technology innovation ability (Xiao et al., 2020), user requirements analysis ability, innovation system construction level, total early-stage entrepreneurial activity (TEA) innovation level, innovation ability of consumption pattern, iterative innovation ability, innovation efficiency level, driving force of manufacturing transformation. The causal loop of the digital collaborative innovation subsystem is shown in Figure 3, which simulates the 'linear models' of innovation that privilege technological supply or restrict the scope of social inquiry into technology to assess its 'impacts'.

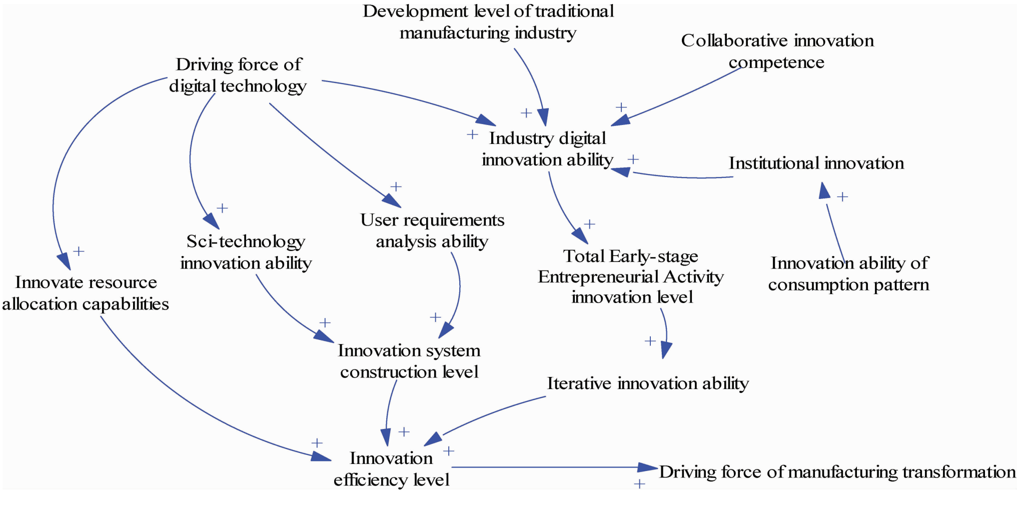


Figure 3 The causal loop diagram of the digital collaborative innovation subsystem

(3) Causal Analysis of digital industry subsystem

In the digital era, the increasing popularity of online commercial activities has provided consumers with more channels and ways to compare and purchase goods (Liu et al., 2021). The development of industrial Internet enables the traditional manufacturing industry to transform into new production modes, such as personalized manufacturing based on consumer demand, service-oriented manufacturing providing value-added services through network collaboration, and collaborative manufacturing, strengthening cooperation between different industrial enterprises. In addition, digital technology can support the improvement of innovation resource allocation efficiency. The innovation of production mode is conducive to breaking the old industrial value chain and reconstructing it. The new industrial value chain can improve the development environment of digital industry and promote progress. As the digital industry grows, increasing digital literacy becomes an urgent task. For example, the EU issued the 2015 EU Digital Skills Declaration and the New Skills Agenda for Europe: Working together to Strengthen Human Capital, Employability and Competitiveness in order to improve the level of digital literacy of the European people, and put forward plans to improve the digital skills of the European people. At the same time, the government provides corresponding digital literacy training and vocational skills training to assist laid-off workers and other specific groups in transferring to employment.

The multiple positive feedback loop of the digital industry subsystem is shown in Figure 4, which has 14 main variables as follows: the development level of Industrial Internet, the level of industrial structure optimization (Shen & Huang, 2020), innovation ability of production mode (Cao, 2018), regional development level, industrial value chain reconstruction ability, consumer digital literacy, digital literacy proficiency, development level of digital industry, allocative efficiency of factors of production, industrial supply capacity, new urban jobs, driving force of digital technology, digital economy industry growth, digital economy scale.

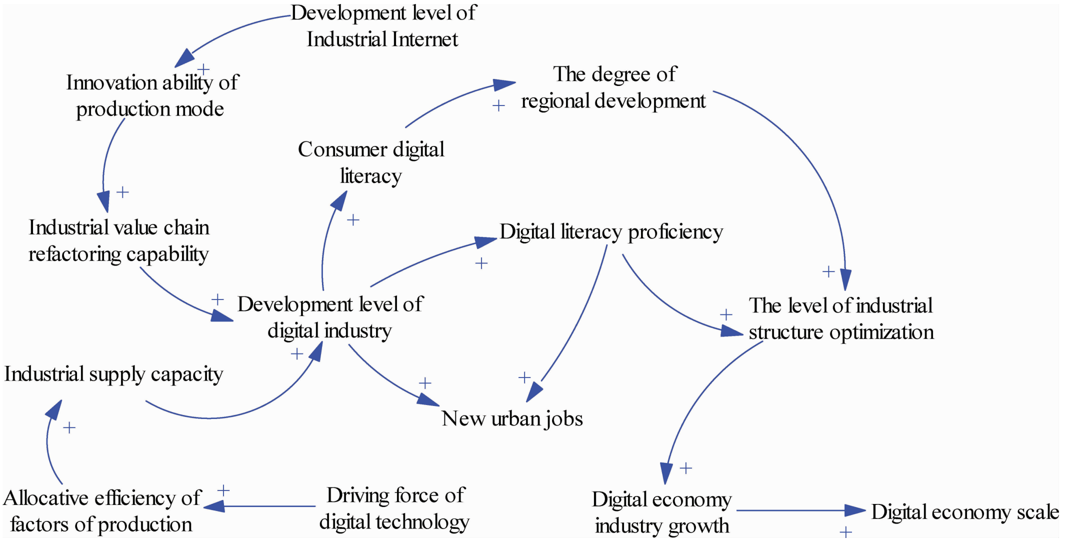


Figure 4 The causal loop diagram of the digital industry subsystem

(4) Causal loop diagrams on manufacturing industry subsystem

The primary issue in supporting the digital transformation of manufacturing industry is bridging the digital divide, which includes both the infrastructure access gap and the digital literacy gap. In the era of digital economy, data production factors with high mobility characteristics play a key role in the digital resource allocation capability of manufacturing industrial enterprises. Wang and Niu (2019) calculates industrial TFP gains of 0.35~0.9 for Chinese industry when the capital and labor are hypothetically reallocated, which equalize marginal products to the extent observed for manufacturing in US. Through the connection of industrial Internet platforms and industrial equipment, it realizes collaborative manufacturing among the manufacturing industries, reduces the acquisition cost of production resources, and improves the utilization range of production resources, so as to achieve digital resource allocation. Enterprises' digital market operation mainly depends on the digital platform, which can serve as the basis for enterprises to obtain market demand and commercial operation services. Therefore, large enterprises need to build their own platforms, while small enterprises can lease platforms. In terms of digital infrastructure, this paper selects the industrial equipment connection index, the development level of the Internet of Things and the development level of digital infrastructure.

Digital technologies, including the IoT, AI, cloud computing, and data center construction, are the source to gather, filter, enhance and transform data across the enterprise to inform every aspect of manufacturing operations (Andrea et al., 2016; Shu et al., 2018), which will become the indispensable parts of the causal loop. There are other main variables in manufacturing industry subsystem as follows: Industrial internet platform development index, the ability of collaborative manufacturing (Cao, 2018), industrial equipment connection index, production resources cost, and production resource utilization capacity (Guo et al., 2020), digital literacy proficiency, bridging capacity of the digital divide (Yan & Sun, 2012), digital resource allocation ability, digital marketing operation level, digital environment support capability, development level of cloud computing, digital density index, total factor productivity (Tian & Lu, 2017). The causal loop of the digital transformation for manufacturing industry subsystem, as the cornerstone of the digital economy, is shown in Figure 5.

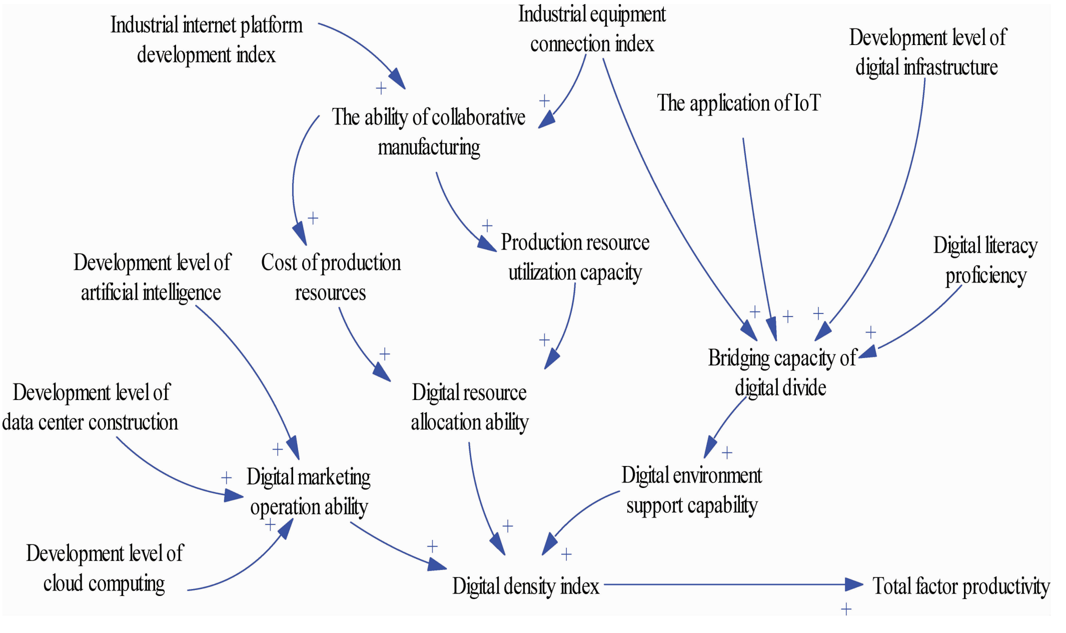


Figure 5 The causal loop diagram of manufacturing industry subsystem

3.2 System Flow Diagram Construction

Vensim PLE can establish the system flow diagram according to the qualitative causal relationship between the parameters of the model variables and realize the simulation prediction of the model variables by giving corresponding initial values or calculation formulas. Because many variables in the system will change over time, the constructed model uses the exogenous variable Time to represent the properties of changing over time for these variables. The equations and the variables of the system flow diagram for the digital transformation of traditional manufacturing industry are as follows :

(1) State variables, also known as cumulative variables or level variables. Its value is cumulative and determined by the rate variable, increasing with the inflow of the rate value and decreasing with the outflow of the rate value. Thus, the value of a state variable at a certain point in time can be summed by adding up past values and rate variables. The equation is expressed as:

$$\begin{aligned} \text{Levels}(t) &= L(t) = L(t_0) + \int_{t_0}^{t} \text{rate}(t)\,dt \\ &= L(t_0) + \int_{t_0}^{t} [\text{inflow}(t) - \text{outflow}(t)]\,dt \end{aligned}$$

Where Levels (*t*) represents the stock value of state variable at time *t*, *rate(t)* represents the change rate of state variable, inflow (*t*) represents the rate value of inflow, and outflow (*t*) represents the rate value of outflow.

(2) Rate variable, which represents the amount of change in the state variable at different moments. The equation can be expressed as:

$$\text{rate}(t) = \frac{d}{dt}\text{Levels}(t)$$
$$\text{rate}(t) = f(\text{Levels}(t), \text{Aux}(t), \text{Data}, \text{Const})$$

(3) Auxiliary variables can be derived from the quantitative relationship between other variable parameters in the system and them. In addition, there is no correlation between the values of auxiliary variables at different moments. The equation can be expressed as:

$$\text{Aux}(t) = g(\text{Levels}(t), \text{Aux}(t), \text{Data}, \text{Const})$$

(4) Constant, which needs to be assigned when the model is initially established and is not affected by other variables or time.

(5) Table functions express non-quantitative relationships that cannot be described by the above types of variables in a customized way. The equation can be expressed as:

$$\text{Lookup name}\left([(X_{min}, X_{max}), (Y_{min}, Y_{max})](X_1, Y_1), (X_2, Y_2), \cdots (X_n, Y_n)\right)$$

Based on the above analysis, the system flow diagram for digital transformation of traditional manufacturing industry can be constructed as the Figure 6.

The system flow diagram and the set of variables are established based on theory of system dynamics, which the causal loop diagrams of digital society, high-technology innovation, manufacturing industry and digital industry are analyzed together with positive feedback of digital transformation for manufacturing industry. The SD model consists of 3 state variables, 3 rate variables, 29 auxiliary variables, 9 constant variables and 5 table functions (Time) shadow variables. The simulation period is from 2014 to 2030, and the simulation step length is

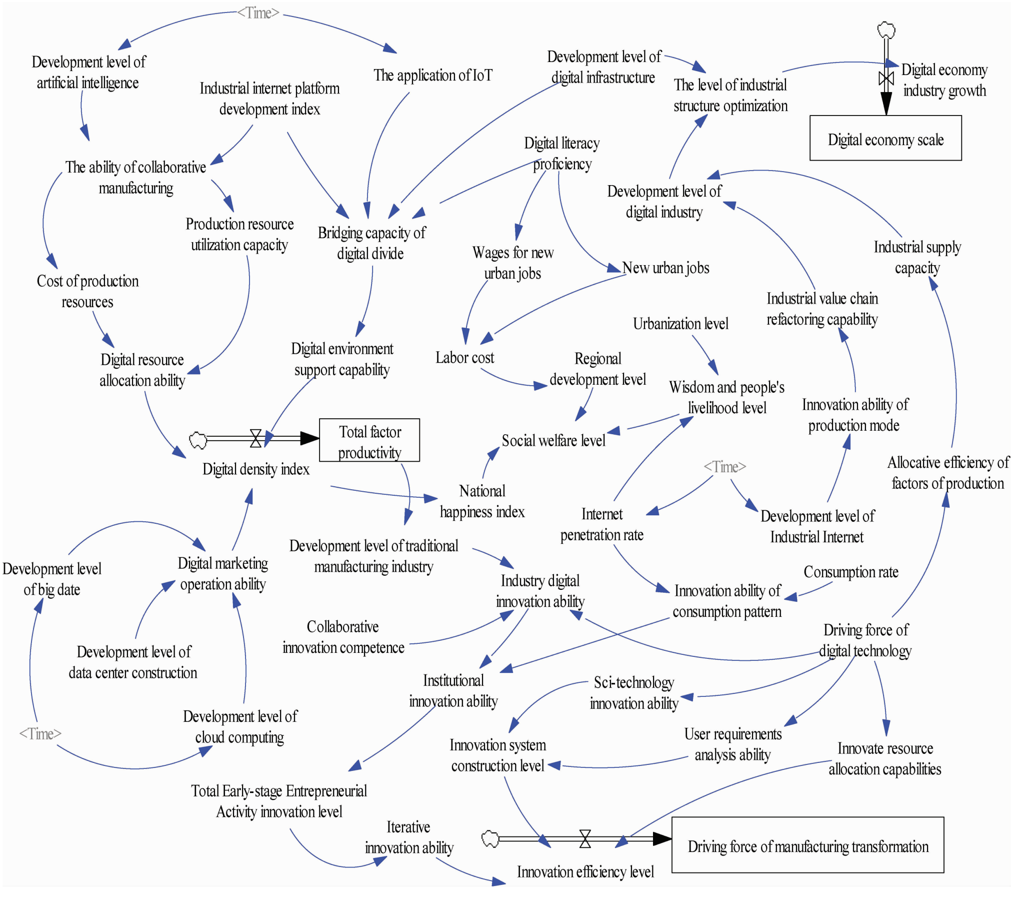


Figure 6 System flow diagram for the digital transformation of traditional manufacturing industry

one year. Statistical analysis software was used for regression analysis to determine the state variables, rate and auxiliary variables of the model, with data source from the 2019 China Internet network development state statistic report, 2019 China Labor Statistical Yearbook, 2018 China Statistical Yearbook, Industrial Internet Platform Development Index (IIP10), White Paper on Cloud Computing Development and White Paper on Internet of Things issued over the years. These equations and variables are shown in Table 1.

Table 1 Equation variables of the simulation dynamics model

Variable (parameter)	Equation (valued)	Unit
Internet penetration rate	WITHLOOKUP(Time,([(2014,46.9%)–(2020,70.4%)],(2014,46.9%),(2015,50.3%),(2016,53.2%),(2017,54.3%),(2018, 59.6%),(2019, 61.2%),(2020, 70.4%))	/
Development level of cloud computing	WITHLOOKUP(Time,([(2014,287)–(2020,2091)],(2014,287),(2015,378),(2016,514.9),(2017,691.6),(2018,962.8),(2019,1334.5),(2020,2091))	100 million yuan

Variable (parameter)	Equation (valued)	Unit
Development level of artificial intelligence	WITHLOOKUP(Time,([(2014,72.7)–(2020,3031)],(2014,72.7),(2015,112.4),(2016,141.9),(2017,216.9),(2018,549.4),(2019,2635),(2020,3031))	100 million yuan
Development level of Industrial Internet	WITHLOOKUP(Time,([(2014,3016)–(2020,31000)],(2014,3016),(2015,4443),(2016,6544),(2017,9640),(2018,14200),(2019,21300),(2020,31000))	100 million yuan
The application of IoT	WITHLOOKUP(Time,([(2014,5679)–(2020,17000)],(2014,5679),(2015,7500),(2016,9500),(2017,11605),(2018,13300),(2019,15450),(2020,17000))	100 million yuan
Total factor productivity	INTEGER(0.997+0.01×Digital density index,0.0227)	/
National happiness index	0.111+0.113×Digital density index	/
Innovation ability of consumption pattern	Consumption rate*Internet penetration rate	/
The level of industrial structure optimization	-1.1102×10^{-16}+6.004×Development level of digital infrastructure+0.354×evelopment level of digital industry	100 million yuan
Digital density index	0.36×Digital marketing operation ability +0.28×Digital resource allocation ability +0.36×Digital environment support capability	/
New urban jobs	7.1054×10^{-15}+142×Digital literacy proficiency	Ten thousand people
labor cost	Wages for new urban jobs×10000÷new urban jobs	Yuan/ Person
Wages for new urban jobs	-2.274×10^{-13}+8191×Digital literacy proficiency	100 million yuan
Industry digital innovation ability	Collaborative innovation competence÷development level of traditional manufacturing industry	/
Institutional innovation ability	Industry digital innovation ability×Innovation ability of consumption pattern	/
Regional development level	1.754×labor cost	Yuan
The ability of collaborative manufacturing	0.5×Industrial internet platform development index+0.5×Industrial equipment connection index	/
Innovation ability of production mode	0.01×development level of Industrial Internet	/
Bridging capacity of digital divide	Digital literacy proficiency ×(Industrial equipment connection index+development level of digital infrastructure +The application of IoT)	/
User requirements analysis ability	1.2566+0.00021×Driving force of digital technology	/
Sci–technology innovation ability	1.3938+0.00024×Driving force of digital technology	/
Innovation system construction level	0.001×User requirements analysis ability×Sci–technology innovation ability	/
Development level of traditional manufacturing industry	195620.3	100 million yuan
Digital literacy proficiency	2.8%	/
Development level of data center construction	1844	Seat
Driving force of digital technology	162000	100 million yuan

3.3 Validation of Simulation Model

The availability of SD model should be testified by comparing simulated data with real data from "China statistical yearbook (2014-2019)" and "White paper of China's digital economy development" of China academy of information and communications technology (CAICT) at April 2021. The SD model can truly reflect the development of digital economy in China from 2014 to 2019, while the experiment results of Table 2 show the deviation of the simulated data and the real data of China's digital economy scale is within ± 5%. Therefore, this paper can use this constructed SD model to simulate the digital transformation of China's traditional manufacturing.

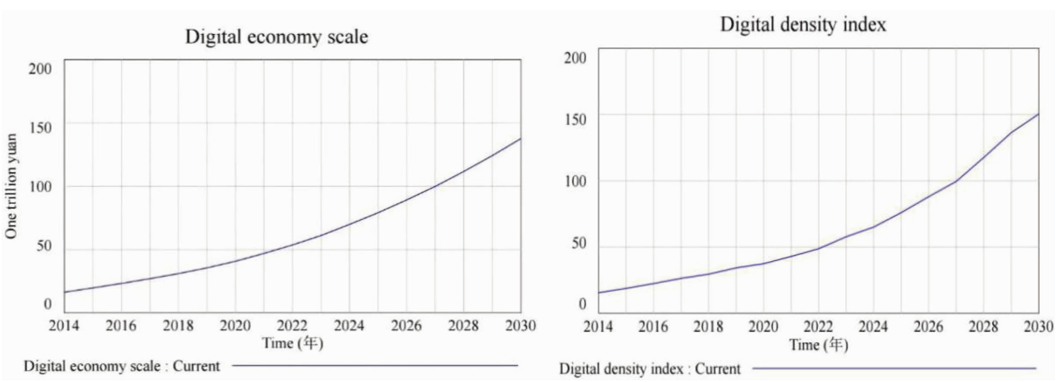
Table 2 Comparison table of China's real and simulated digital economy scale from 2014 to 2019

Year	Real Value(Trillion Yuan)	Simulated Value (Trillion Yuan)	Relative Error(%)
2014	16.2	16.2	0
2015	18.6	19.51	4.89
2016	22.6	23.16	2.48
2017	27.2	26.92	–1.02
2018	31.3	30.99	–0.99
2019	35.8	35.50	–0.84
2020	39.2	40.73	3.90

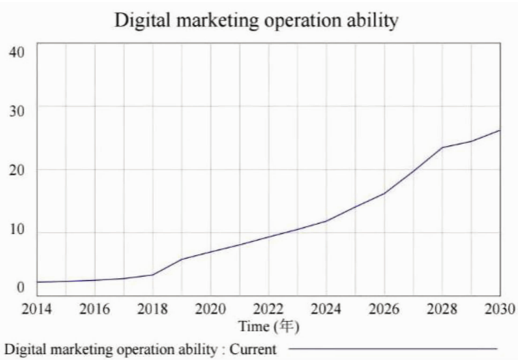
4 Experiments and Analysis

4.1 Simulated experiment based on SD model

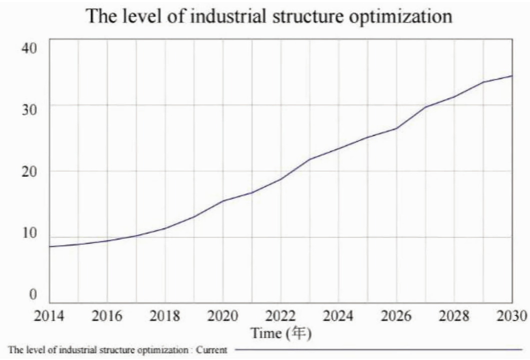
The Vensim PLE platform gives an opportunity to explore the digital transformation behavior of traditional manufacturing based on feedback systems theory and analytical approach, where each variable can be visualized independently with complements systems thinking. This paper makes a simulated experiment of the unbalanced growth of traditional manufacturing industry from the perspective of the digital economy, marketing, digital density, etc., according to China's national statistical data sample between 2014 and 2019, as shown in Figure 7.



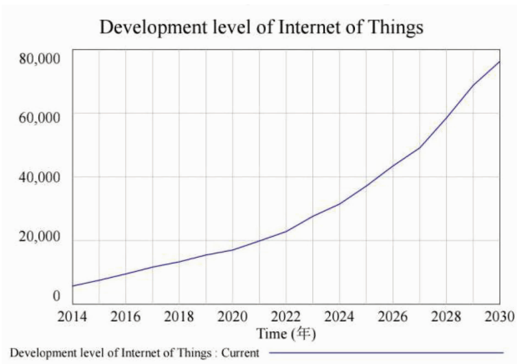
(a)Growth trend of digital economy scale (b)Development trend of digital density



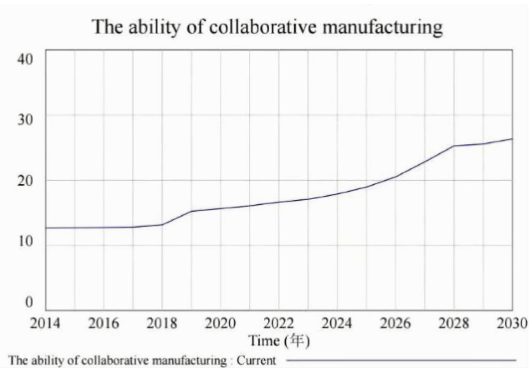
(c)The level of digital market operation



(d) The level of industrial structure optimization



(e)The application trend of Internet of Things



(f)The ability trend of collaborative manufacturing

Figure 7 The digital transformation development trend of traditional manufacturing industry

As China's traditional manufacturing embark on its journey to Industry 4.0, digitalization is accelerated to optimize, modernize and automate, which has led to increasing scale of digital economy and the digital density in the last ten years. Figure 7(a-b) indicates that the digital transformation of China's manufacturing industry is progressing rapidly. The digital density index can help to gauge the current digital density of an economy and guide digital investments in business, while the index value of networked and intelligent development is low. China's traditional manufacturing harness the power of data-real-time market operation and creation of new revenue stream, shown as in Figure 7(c-d). In the future, the application of the industrial internet of things will further accelerate the digitalization of supply chains and promote collaborative manufacturing capability through objects interacting with objects and humans to optimize processes or create new product and service hybrids, as shown in Figure 7 (e-f). However, the accumulation of intelligent manufacturing in traditional manufacturing industry is weak, and the integrated innovation of management and technology is not enough in the digital disruption era. Such profiles can be an important starting point for government and industry leaders as they shape and implement digital strategies and optimize the industrial structure.

4.2 Experiment analysis by adjusting the influencing factors

The system dynamics conduct simulation experiments by adjusting the variable coefficients of the constructed model to simulate the changing trend of system behavior under different strategies, which can be helpful for getting a quick impression of the effects of intended policy changes. It allows observing the changes that influence the entire model by adjusting the public policy factor, technology innovation factor, as well as an industrial digital ecosystem. These models are used to visualize the effects of intended policies by analyzing the causal diagram, system flow diagram of every sub-systems.

(1) The analysis of total factor productivity (TFP) influenced by the digital density.

In the Accenture digital density index, digital density is explained as the widespread use of digital technologies and activities and the extent to which "digital" technologies are used in businesses, institutions and economic environments. In the field of manufacturing, the focus has shifted from increased production to increased productivity, then to automation, reaching connectivity through the use of cyber-physical systems in production processes. The digital density and digital literacy of practitioners have a positive effect on the China's traditional manufacturing industry. Increasing the specialization level of the industry has a positive effect on the growth of the TFP in labor-intensive industries. Digital literacy skills encompass an intricate system of knowledge, skills, abilities, and motivational factors that must be developed according to the needs of their specific domains. The populations where digital literacy is most important are ICT users, e-business professionals, and ICT professionals. Estonia's nationwide program called Programming Tiger teaches children aged 7 to 19 how to write software code, aiming at developing digital skills to improve employability. The simulation experiment promotes total factor productivity (TFP) by adjusting the digital density factor, as shown in Figure 8.

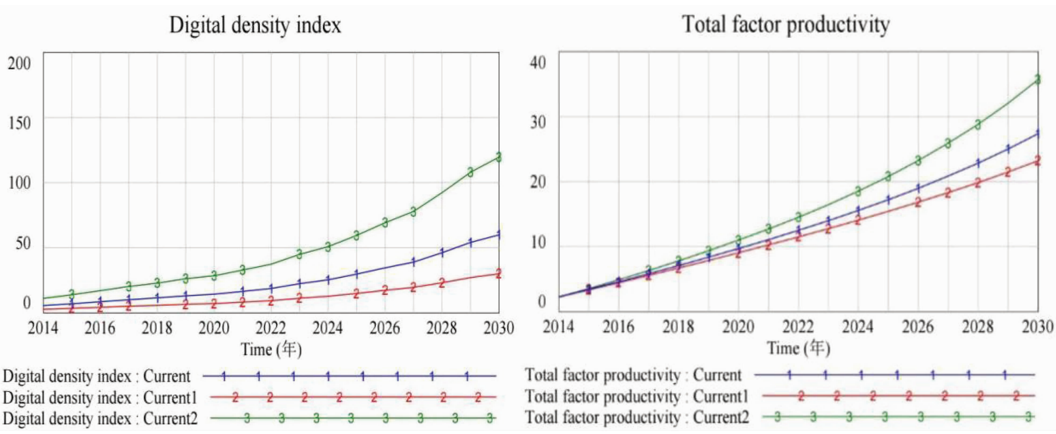


Figure 8 The analysis of total factor productivity influenced by the digital density

The Current, Current1, and Current2 represent the normal, upper and lower level of total factor productivity (TFP), which the digital literacy factor are 0.28, 0.14 and 0.56. The increase in digital density has greatly improved the efficiency of design, production, sales and transportation, which has greatly reduced inventories and accelerated the growth of total factor productivity. According to the different development stages of labor-intensive enterprises, It is necessary to strengthen the ability of employees to develop and use data, so that data can play a greater utility value. From the production, storage, maintenance and other aspects, strengthen the skills training of workers and the ability of data management and control. In the process of digital transform, it is necessary to strengthen the training and development of talents, endow the staff with the skills and knowledge of value creation, and stimulate the initiative and potential of staff value creation to increase productivity and agility of China's traditional manufacturing industry.

(2) The analysis of digital transform capability influenced by collaborative innovation

To keep growing and upgrading, the capital-intensive manufacturing industry and IT Companies should increase their use of talent and technology innovation to transform key business processes to create greater leaps in efficiency and productivity. The most perspective directions of technology innovation in the manufacturing industry are a collection of social goods and services, marketing studies, and promotion of social goods and services. The simulation experiment of digital transform capability by adjusting the technology collaborative innovation factor, is shown in Figure 9. The Current, Current1, and Current2 represent the lower, normal and upper levels of digital transform capability, when the collaborative innovation factor are 14.718, 7 and 30.

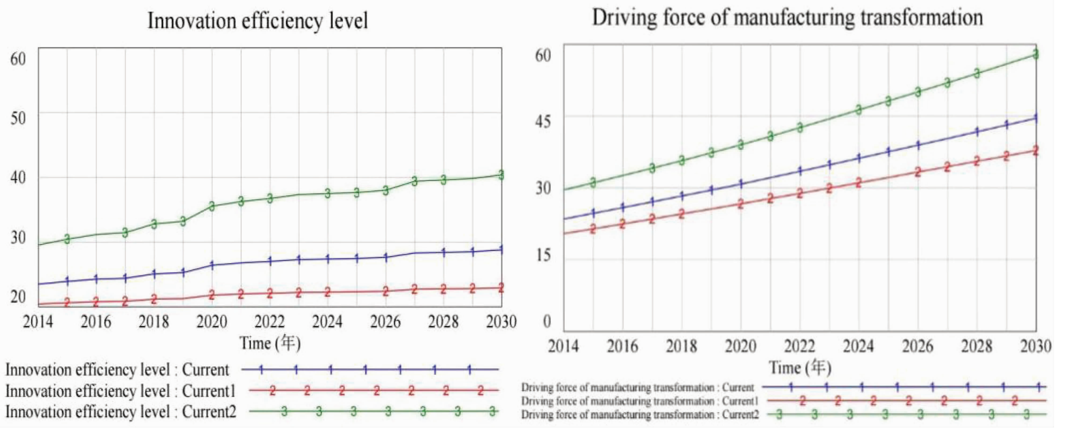


Figure 9 The trend of digital transform capability influenced by collaborative innovation

The traditional manufacturing industry can have a more comprehensive digital transform capability based on the accumulation of digital-technology collaborative innovation. Investment-innovation transforming factor plays the key role in digital transform capability of China's manufacturing industry, as shown in Figure 9, especially in the capability of R&D, manufacturing, and transforming capital investment into technical innovation achievement in the future. The application of digital technology innovation can enable enterprises to carry out flexible production and realize large-scale personalized, customized service, which the digitally-integrated and intelligent value chain is vital to drive innovation and become customer-centric. In terms of tactic layout, the previous operation model of the manufacturing industry should be fundamentally reformed, and the digitalized means, including the Internet, artificial intelligence, and Internet of Things, should be employed to arm different links of enterprises, such as R&D, production, and marketing. In terms of product R&D, with the digital design, simulation and optimization of the product's entire life cycle based on digital technology, IT Companies help manufacturing enterprises conduct R&D digitally to realize product innovations. The cooperative-innovation approaches are not equal to the simple introduction and application of digital technologies but the digitalization of the whole product creation process to form a more efficient, concise, and profitable operation model. The collaborative innovation of digital technology has reconstructed the management mode of the traditional manufacturing industry, which ensures the high efficiency and timeliness of digital transformation.

(3) The analysis of bridging the digital divide influenced by the digital infrastructure.

The transformation of the technology-intensive traditional manufacturing industry needs perfect infrastructure, such as ICT, IoT, and Industrial Internet infrastructure, which can realize the data collection, information transmission, and production tasks in the manufacturing process. The priority given to their digital infrastructure development can bring a greater integration of digital technology and manufacturing.

The simulation experiment of building bridges the digital divide by adjusting the digital infrastructure factor, as shown in Figure 10. The Current, Current1, Current2 represent the lower, normal and upper level of digital capacity building to bridge the digital divide, when the digital-infrastructure factor are 0.6, 1.2 and 2.4.

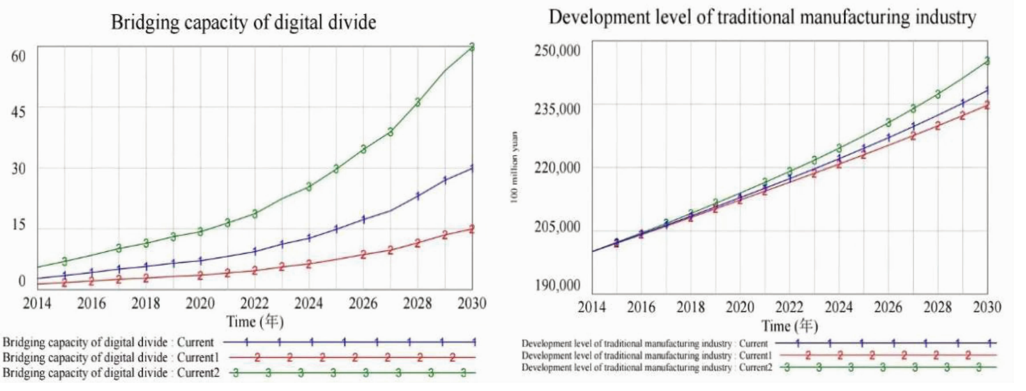


Figure 10 The analysis of bridge the digital divide influenced by digital-infrastructure

The digital infrastructure helps consumers reduce search time and transaction information costs, and push manufacturing enterprises to provide consumer-centered services. The digital economy has broken transaction's temporal and spatial restrictions of traditional manufacturing enterprises, changed the one-way passive conduction mode from enterprise to consumer into the bidirectionally connected and positive model of enterprise and consumer. Traditional manufacture industrial will have a number of different machines and processes placed in a plant or shop floor. The explosion in connected devices and platforms, the abundance of data from field devices and rapidly changing technological landscape has made it imperative for companies to quickly tailor their products and services and move from physical world to a digital world. Such obstacles have diminished dramatically with IoT services and EI 4.0 solutions , effectively increasing the value-added business value of manufacturing. With the application of AI and the Industrial Internet, it realizes data sharing in productivity and production mode. Industrial Internet applications grant free access to enterprise data, which has redefined the life cycle of manufactured products. Through data sharing, the status monitoring, efficiency analysis, remote diagnosis and history tracing of the production site can be realized. In the age of digital economy, it is urgent for manufacturing enterprises to develop industrial internet and promote intelligent manufacturing, bridging the physical-digital divide with the platform of Internet of things and solutions.

5 Conclusion and Countermeasures

This paper analyzes influencing factors and inner logical relationship of the digital transformation for China's traditional manufacturing industry based on the SST theory framework, which is divided into four correlative systems, economy, policies, mobile technologies and industrial chain through the sociotechnical systems approach. We construct the system dynamics model to simulate the development of China's traditional manufacturing industry by Vensim software, which conduct the policy experiments of digital literacy education, industrial policy of various industry alliances, digital innovation and technology investment. Therefore, this paper proposes some suggestions for the digital transformation of traditional manufacturing industry from the perspectives of enterprises and government: (1) China's government should alleviate the innovation burden of enterprises by means of gradient tax cuts and fee reductions in order to optimize the digital business environment of traditional manufacturing industry, capturing the digital - driven technology innovation by relevant laws and regulations; (2) The digital density and digital literacy of practitioner have the greatest impact on the digital transformation of traditional manufacturing enterprises. The education department should strengthen digital literacy education in educational institutions to make digital literacy a necessary quality for the young generation, and cultivates high-end digital technical talents by holding competitions and intensive training in universities; (3)Based on the advantages of Industrial Internet, Industry 4.0, artificial intelligence and other digital technologies, the traditional manufacturing industry should reconstruct the value chain through the digital platforms, which focuses on building Industrial Internet Consortium (IIC), intelligent operation and the digital supply chain by support open standards and industry frameworks emerging from various industry alliances; (4)Furthermore, the traditional manufacturing industry should use industry 4.0 (IE4.0), big data analytics and IOT technologies to develop the supply chain resilience and provide real-time information on various supply chain activities, which can mitigate risks related to COVID-19 and accelerate the digital transformation of manufacturing industry.

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