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A Capability Maturity Model for Intelligent Manufacturing in Chair Industry Enterprises

Wanqiang Wang [1,2], Jiadong Wang [1], Chang Chen [1,2], Shaohui Su [1,2,*], Changyong Chu [1,2] and Guojin Chen [1,2]

1 School of Mechanical Engineering, Hangzhou Dianzi University, Hangzhou 310018, China; wwq@hdu.edu.cn (W.W.); wangjd@hdu.edu.cn (J.W.); chenchang@hdu.edu.cn (C.C.); kevin@hdu.edu.cn (C.C.); chenguojin@163.com (G.C.)
2 Anji Intelligent Manufacturing Technology Research Institute, Hangzhou Dianzi University, Huzhou 313300, China
* Correspondence: sshhui@hdu.edu.cn

Abstract: Intelligent manufacturing has a strong role in promoting the transformation and upgrading of traditional industries such as the chair industry. This study aimed to accurately evaluate the production status and technical level of chair industry enterprises, and then better guide chair industry enterprises to gradually implement intelligent manufacturing. Based on the analytic network process (ANP), we propose four capability domains, nine capability sub-domains, and 21 evaluation elements, thereby constructing an evaluation model for the capability maturity of chair industry enterprises' intelligent manufacturing. First, the weight relationship of each index of the model was determined by means of an expert questionnaire. Then, super decision software was used to complete the modeling of the evaluation index of the network analytic hierarchy process. Finally, the evaluation model of the intelligent manufacturing maturity of chair industry enterprises was applied to 50 chair industry enterprises for evaluation and verification, and the evaluation results of the model proposed in this paper were compared with the evaluation results of the intelligent manufacturing maturity model released by China's national standards. The results show that the evaluation model constructed in this study can better reflect the development status and overall technical level of intelligent manufacturing in the chair industry. Furthermore, the evaluation results can provide decision-making suggestions for chair industry enterprises to identify important areas for improvement and implementation of intelligent manufacturing upgrade plans.

Keywords: intelligent manufacturing; maturity assessment; analytic network process; chair industry; comprehensive evaluation model

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Citation: Wang, W.; Wang, J.; Chen, C.; Su, S.; Chu, C.; Chen, G. A Capability Maturity Model for Intelligent Manufacturing in Chair Industry Enterprises. *Processes* **2022**, *10*, 1180. https://doi.org/10.3390/pr10061180

Received: 20 May 2022
Accepted: 10 June 2022
Published: 13 June 2022

1. Introduction

The manufacturing industry has become more complex, and manufacturing systems have evolved to a level that is smarter, more flexible, more mass-customizable, more efficient, and of better quality. Industrialized countries around the world have realized the importance of technology and innovation to improve operational efficiency, and of transforming traditional resources into smart objects, enabling them to perceive, act, and perform well in intelligent environments [1]. This is being achieved by extensively supporting and integrating the latest advanced technologies, such as Internet of Things, Cyber-Physical Systems (CPSs), Information and Communication Technology (ICT), Cloud Computing (CC), Digital Twins and Big Data Analytics (BDA). The proper synchronization of these technologies has brought about a paradigm shift in manufacturing [2], leading to the emergence of "Industry 4.0 (Germany and European Union), Industrial Internet of Things (IIoT) and Smart Manufacturing (USA), Smart Factory (Japan and Korea) and Intelligent manufacturing (China)", and other concepts. The concepts differ very little, other than being implemented in different countries/regions, and they all have their own plans/courses of action. Regardless of how the concept is defined, it implies a key goal of improving businesses in different countries and their manufacturing environments to connect and embrace technological advancements in information and operational technology. This lofty goal is expected to foster a steady flow of revenue while reducing associated costs and increasing efficiency.

As an important pillar of the national economy, manufacturing has promoted the rapid and high-quality development of society, and is the main source of industrial innovation and improvement of people's lives. However, international trade frictions, the continuous development and application of new technologies, and the increasing cost of production factors have gradually weakened the advantages of traditional manufacturing [3,4]. The fourth industrial revolution swept the world and promoted the transformation and upgrading of traditional manufacturing to intelligent manufacturing [5–7]. Smart manufacturing technology originated from the introduction of the term "Industry 4.0 (Fourth Industrial Revolution)" and was pioneered by the Smart Manufacturing Leadership Consortium (SMLC), which defined it as "a set of manufacturing practices designed to shape a new round of networked data and information technology capabilities for future manufacturing operations." China also provided the definition of intelligent manufacturing in the "Intelligent Manufacturing Development Plan (2016–2020)": intelligent manufacturing is based on a new generation of information and communication technology. It is deeply integrated with advanced manufacturing technology and runs through all aspects of manufacturing activities such as design, production, management, and service. It is a new production method having functions such as self-perception, self-learning, self-decision making, self-execution, and self-adaptation [8].

Smart transformation provides a key driving force for manufacturing, especially smart manufacturing [9]. It promotes the intelligent transformation of enterprises, and helps enterprises develop new business models to improve products, organizational structures or processes [10], information and knowledge sharing, and seize market opportunities. Currently, leading manufacturing companies are answering the call and embarking on a journey to implement the smart factory concept. Automaker Tesla has built a smart factory in which a network of devices, sensors and robots work together within an integrated system to more efficiently produce cars and batteries. Swedish truck manufacturer Scania has traditionally maintained its competitiveness through innovations in production processes (for example, by pioneering the integration of industrial robots, programmable logic controllers (PLC), CAD/CAM and lean management techniques), and now is seeking to transform the way it operates through smart factory technology [11]. Despite the hype around Industry 4.0, smart manufacturing and smart factory concepts, and Smart Manufacturing Systems (SMSs) proving their potential in various ways, Canetta, Barni and Montini [12] mention that many companies implementing Industry 4.0 have encountered a challenge. According to Rajnai and Kocsis [13] and Sony and Naik [14], some entrepreneurs are unaware of the current industrial digitization trends, and some leaders have no idea how to implement industrial digitization. Many small and medium enterprises (SMEs) still struggle to understand the complexities offered by smart manufacturing(SM) and are not ready to embrace the concepts of SM [15]. Furthermore, many SMEs still lack knowledge about the application of technology to business, production and supply chains. These enterprises are the backbone of economic growth and, therefore, must apply advanced technology to their business and operations to increase productivity.

Therefore, the assessment of intelligent manufacturing maturity has become an indispensable tool for manufacturing enterprises, especially small and medium-sized enterprises. Since entrepreneurs are uncertain about the impact of Industry 4.0 technologies [16], maturity assessment is an appropriate method to reduce uncertainty in investing in technologies [17]. Maturity assessments are usually conducted based on a self-assessment, and in this self-assessment, the possible information gathered includes understanding, awareness, perception, current practices, and the organization's attitudes.

At present, many scholars and research institutions have carried out a large amount of research on the evaluation of intelligent manufacturing capability, and proposed the maturity model and evaluation method of intelligent manufacturing capability.

1.1. Research Status of Intelligent Manufacturing Capability Maturity Model

The National Standardization Administration of China has released a general intelligent manufacturing capability maturity model [18] and evaluation method [19] for the manufacturing industry, but the model and evaluation method cannot make targeted evaluations based on the characteristics of each industry. Du Jinsong and others set up the unweighted super matrix, weighted super matrix, and extreme weighted super matrix based on the background of garment enterprises, and realized the comprehensive evaluation process based on the ANP model for the maturity of intelligent manufacturing capability of garment enterprises [20,21]. The Ren Wei team of Sinopec Group proposed an intelligent manufacturing capability maturity model for the petrochemical industry based on the specific practice of intelligent manufacturing in the petrochemical industry [22]. Ren Junfei and others proposed a two-level fuzzy comprehensive evaluation method based on AHP to evaluate the maturity of intelligent manufacturing capabilities of manufacturing enterprises [23]. Yi Weiming and others established a three-dimensional index system for evaluating enterprise intelligent manufacturing capabilities based on tensor theory, and constructed an evaluation model for intelligent manufacturing capabilities [24]. Su Qingfu and others, based on the Chinese national standard, established an evaluation model of intelligent manufacturing capability maturity, combined with the characteristics of the automobile industry, adding the fields of culture, supply chain, and logistics capabilities, and proposed an evaluation index of intelligent manufacturing capability maturity unique to the automobile industry [25]. The model proposed by Syed Radzi Bin Rahamaddulla and others is enhanced with 4M attributes as the dimension and embedded with the characteristics of Industry 4.0 components to help SMEs overcome the possible uncertainties in adopting the SM concept [26]. Shan Wu and others constructed a composite dual innovation capability model for intelligent manufacturing enterprises, and provided model evaluation indicators for a reference. This model is a popular research topic and provides a theoretical framework for follow-up research on the innovation capability of intelligent manufacturing enterprises, and promotes the innovation and development of intelligent manufacturing enterprises [27]. Nilubon Chonsawat and others proposed the Smart SME 4.0 Maturity Model and used it to assess the readiness of a project to enter the field of smart manufacturing. The model was implemented in two company cases in Thailand, and the results show that the model can assess organizational readiness and guide companies to effectively implement Smart SME 4.0 [28].

1.2. Research Status of Other Related Maturity Models

Based on the literature research method, expert questionnaire method, Delphi method, and other methods to construct the index system, and referring to the basic ideas of other maturity models, the Jingyi Hu team proposed a conceptual model based on capability elements, maturity level and maturity requirements [29]. Xu Guibao's team constructed an enterprise "Internet+" capability maturity (CMI+) model based on the eTOM model. The study proposed an evaluation index based on the above model and a specific evaluation method for each index, which can be used to guide enterprises to improve intelligent manufacturing capacity [30]. Geng Chao and others proposed a maturity model of a complex digital industrial system based on systems engineering theory, covering industrial systems, development models, implementation points and primary conditions [31]. Focusing on digital investigation, Martin Kerrigan and others proposed a Digital Investigation Capability Maturity Model (DI-CMM) [32] that includes people, processes, and technology as the primary factors for evaluating capabilities. Based on the principle of innovation diffusion established by Everett Rodgers, the Bass diffusion curve, and living (ecological) system theory, Oliver Schwabe and others proposed a maturity model. This model is used to predict the innovation diffusion rate of flexible mass customization businesses in the manufacturing industry, and the validity of the model was proved with multiple sets of evaluation variables [33]. Xiao Jijun and others constructed an improved Discrete Hopfield Neural Network (DHNN) evaluation model based on AHP, and obtained the maturity levels of five regions to be classified [34]. According to domestic and foreign technology maturity assessment methods, Ren Jing and others constructed a shipbuilding technology maturity assessment system [35]. Assel Yezhebay et al. proposed an evaluation model consisting of six dimensions and 15 sub-dimensions by revising the existing digital maturity model [36].

From the analysis of the above research status, it can be seen that a general maturity evaluation model exits for the manufacturing industry, and there are also industry evaluation models that are combined with industry characteristics when evaluating the maturity of intelligent manufacturing capabilities in different industries. At present, China is the world's second-largest economy, and is also the world's largest chair production base; hence, the focus of this study is China's chair industry. At present, the intelligent manufacturing capability maturity model issued by the National Standardization Administration cannot be evaluated according to the characteristics of the chair industry, and the evaluation results will thus also have some errors. Moreover, currently, there is no evaluation model for the chair industry. This study combined the "Intelligent Manufacturing Capability Maturity Model" (GB/T39116-2020) [18] and "Intelligent Manufacturing Capability Maturity Assessment Method" (GB/T39117-2020) [19], two Chinese national standards, and the characteristics of chair industry enterprises to establish a chair industry intelligent manufacturing maturity model and evaluation method. This model shows the gap between the current chair industry enterprises and the highest goal of intelligent manufacturing, and provides effective method guidance for the improvement of intelligent manufacturing capabilities and high-quality development of chair industry enterprises. The structure of this paper is as follows: Section 2 presents the characteristics of the chair industry. Section 3 introduces the construction of the evaluation index system, and Section 4 introduces the intelligent manufacturing capability maturity model of chair industry enterprises. Section 5 describes the application implementation of the model on 50 enterprises. Finally, Section 6 presents our results and conclusions. The overall workflow of this paper is shown in Figure 1.

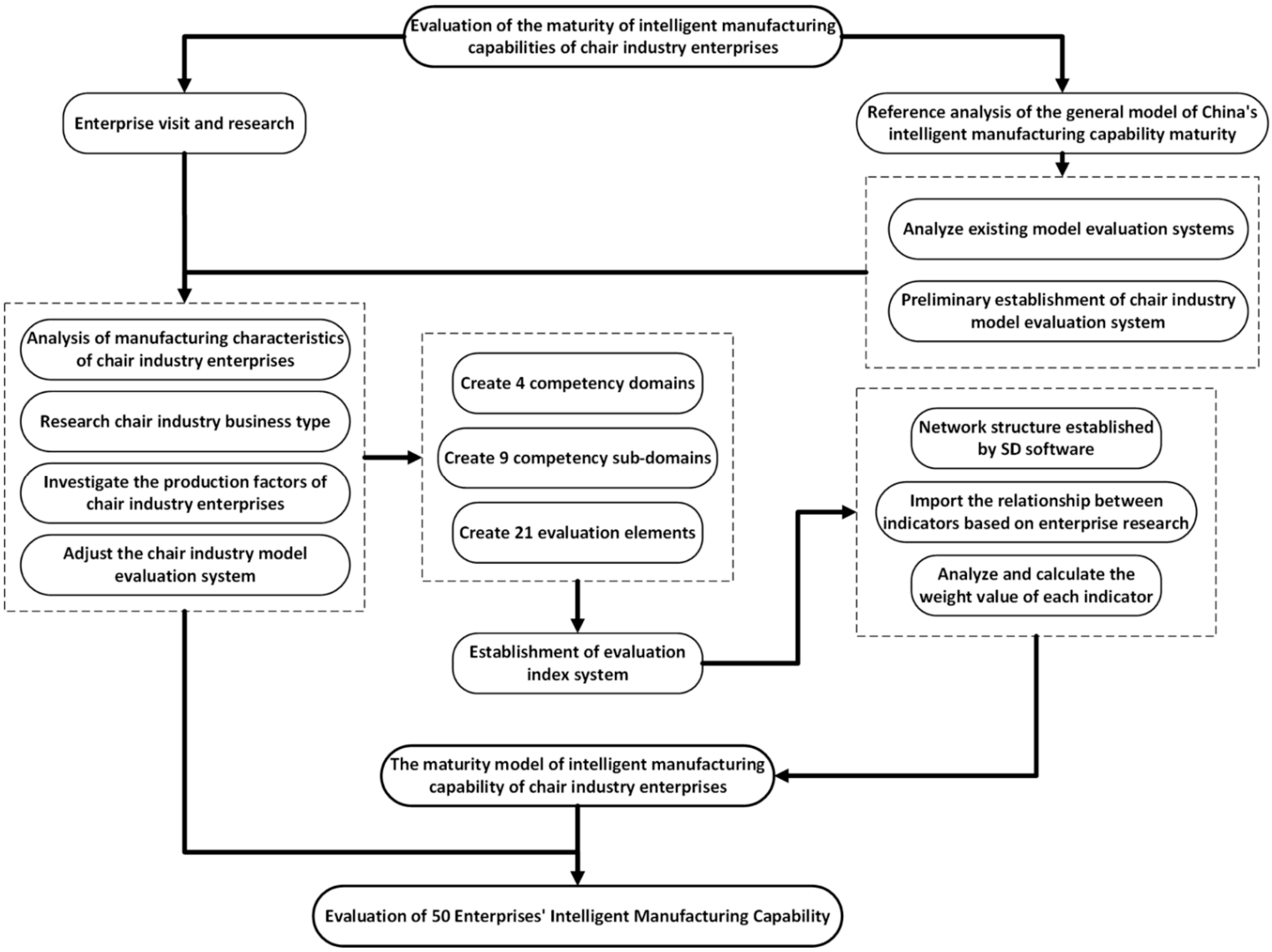


Figure 1. Workflow block diagram.

2. Product Design and Manufacturing Characteristics of Chair Industry Enterprises

Chair industry enterprises are typical multi-variety small-batch production enterprises, and their intelligent manufacturing characteristics are listed as follows:

- In terms of design: The product structure is simple, and the design process mainly includes human factors engineering and industrial design processes. On the premise of satisfying the basic functions, the comfort of the seat is improved, and the health of the user is promoted; at the same time, proofing and modeling design are carried out, adding industrial design elements to meet the aesthetic needs of different customers; in order to meet the needs of personalized customization of products, the company adopts modular design technology.

Application of intelligent manufacturing-related technologies: chair industry product design system for human factors engineering, modular design system.

- In terms of production and manufacturing: due to the existence of a large number of fabric and sponge parts, the production process has a low degree of automation, and a large amount of labor is used; metal, plastic, fabric, and sponge parts belong to different production lines, which makes production planning and scheduling more complex, and it is challenging to coordinate the production operations and production rhythms of each production line; there are many kinds of raw materials, which are difficult to store and distribute; and some processes have harsh production environments, such as spraying. Therefore, most chair industry enterprises only use automation equipment in some key production links, or establish an assembly line for the entire production process for certain chairs, and cannot establish an automated production line for all products; in order to improve the efficiency of warehousing and distribution, enterprises began to establish intelligent warehousing systems.

Intelligent manufacturing-related technology applications: automated hanging lines, intelligent manufacturing equipment units, manufacturing execution management systems, intelligent warehousing, etc.

- In terms of sales and service: the variety of products makes sales and service difficult.

Intelligent manufacturing-related technology applications: online sales platform, customer relationship management system, product customization service system, etc.

- Informatization of the manufacturing industry: In order to improve the level of enterprise informatization management and realize the intercommunication and integration of enterprise data, some enterprises have begun to implement ERP systems and PLM systems.

Intelligent manufacturing-related technology applications: ERP systems, PLM systems, cloud platform, etc.

In response to these industry challenges, chair industry companies have improved their innovation capabilities and manufacturing level by introducing intelligent manufacturing technology. The application of intelligent manufacturing technology in the chair industry is shown in Figure 2.

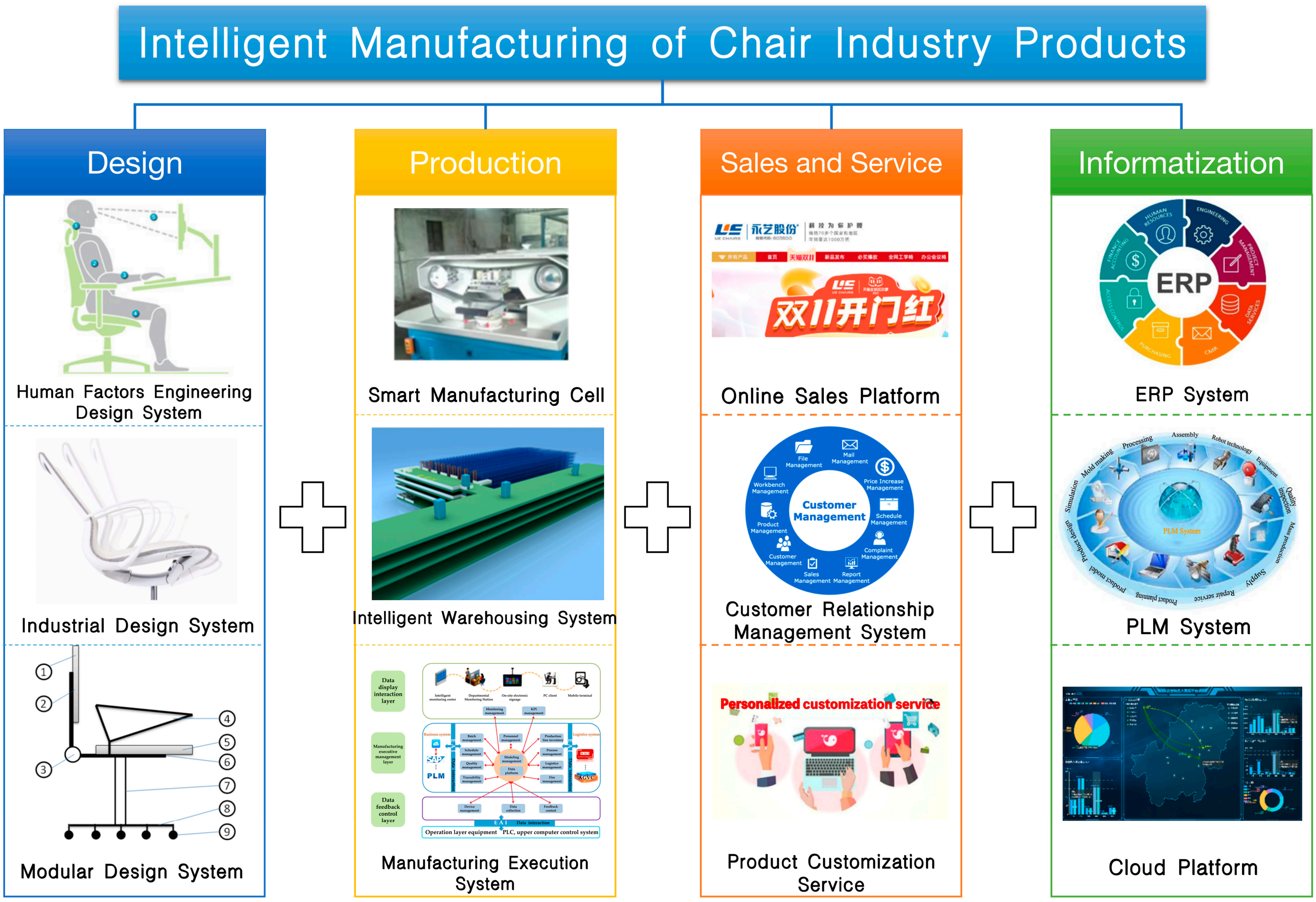


Figure 2. Application of intelligent manufacturing technology in the chair industry.

3. Evaluation Index System of Intelligent Manufacturing Capability Maturity of Chair Industry Enterprises

3.1. Intelligent Manufacturing Capability Maturity Evaluation Classification

According to the five evaluation grading principles of planning level, specification level, integration level, optimization level, and leading level in the intelligent manufacturing capability maturity evaluation method [19], and the Industry 4.0 readiness model [37], the intelligent manufacturing capability maturity of chair enterprises is divided into five categories. There are five grades, as shown in Table 1. The larger the number in the table, the higher the maturity level and the stronger the intelligent manufacturing capability, and vice versa.

Table 1. Maturity levels and descriptions.

Intelligent Manufacturing Level	Corresponding Scoring Interval	Level Description
Planning level	$0.8 \leq S < 1.8$	Enterprises have begun to plan and invest in intelligent manufacturing, and informatization has been realized in some core links.
Normative level	$1.8 \leq S < 2.8$	Enterprises can apply digital equipment, IT systems and integrate core business areas, and can achieve information sharing within a single business.
Integration level	$2.8 \leq S < 3.8$	Enterprises have achieved integration between some core businesses, and data can be shared within the enterprise.
Optimized level	$3.8 \leq S < 4.8$	Data mining can be carried out to achieve the application of knowledge and models, and it can feedback and optimize the process of core business, and begin to embody artificial intelligence.
Leading level	$4.8 \leq S \leq 5$	Enterprises can carry out prediction, early warning and self-adaptation, and realize the innovation of the industrial model through the horizontal integration with the upstream and downstream of the industrial chain.

3.2. Establishment of Intelligent Manufacturing Capability Evaluation Index System

Based on the national standard of the intelligent manufacturing capability maturity model and the characteristics of the chair industry, the design, production, sales, service, and other link elements are taken as the capability domain of the intelligent manufacturing capability maturity of the chair industry. By analyzing the process characteristics of each manufacturing element, nine elements were obtained as capability sub-fields; 21 evaluation elements were then screened out on this basis; finally, an evaluation index system was formed; this process is shown in Table 2. The score results of each evaluation element affect the score of its corresponding capability domain, and the score result of the capability domain becomes an important reference index for considering intelligent manufacturing capabilities.

Table 2. Evaluation indicators of the intelligent manufacturing capability of chair industry enterprises.

Competency Domain		Capability Subdomain		Evaluation Elements		Illustrate
Name	**NO.**	**Name**	**NO.**	**Name**	**NO.**	
Design	A	Product Design	A1	Human Factors Engineering	A11	Evaluate the ability to design healthy seating and seat comfort based on ergonomics and a database of basic human parameters
				Industrial Design	A12	Evaluate the ability of seat exterior styling design based on design knowledge base and existing product database
				Modular Design	A13	Evaluate the ability of modular design based on design knowledge base and existing product parts library
				Integration with PLM/ERP System	A14	Evaluate the ability of enterprises to realize collaborative design of various departments based on CAD/PLM/ERP integration, and through design data storage, management and circulation
		Technological Design	A2	Process Database	A21	Evaluate the enterprises' ability to establish a seat production craft database, or craft product data structuring, and evaluate the enterprises' ability to share and reuse craft data
				Process Standardization	A22	Evaluate the repeatability of the production craft and the ability to standardize the production craft process
Production	B	Production Work	B1	Production Automation	B11	Evaluate the degree of automation of production equipment and the degree of intelligent manufacturing of seat production lines
				Production Capacity	B12	Evaluate the production level and production efficiency of seat products
		Production Control	B2	Order Management	B21	Evaluate order management capabilities, including order production, order tracking, order delivery, etc.
				Planning and Scheduling	B22	Evaluate the ability of seat enterprises to establish a standard working hour database according to constraints (production process, delivery time, processing resources, etc.) to realize automatic production scheduling and scheduling optimization
				Quality Control	B23	Evaluate the ability of seat enterprises to monitor and manage the quality of raw materials, work-in-process and seat products in real time, and to analyze and improve the quality

Table 2. *Cont.*

Competency Domain		Capability Subdomain		Evaluation Elements		Illustrate
Name	**NO.**	**Name**	**NO.**	**Name**	**NO.**	
		Material Management	B3	Purchasing Management	B31	Evaluate the ability of seat companies and suppliers to connect order information in a timely manner, including risk monitoring in the procurement process, independent feedback and adjustments, etc.
				Warehousing and Distribution	B32	Evaluate the intelligence of enterprise warehousing and distribution, including automatic warehousing, instant distribution, inventory management, etc., to achieve inventory optimization
				Device Management	B33	Evaluate the detection, early warning and maintenance of key equipment in the production process of seat enterprises, realize real-time monitoring and remote monitoring of equipment, and carry out fault prediction and early warning
Sale	C	Sales Management	C1	Sales Plan	C11	Evaluate enterprise sales planning capabilities, including optimizing customer needs, formulating accurate sales plans, and implementing sales historical data management and analysis applications.
				Sales Platform	C12	Evaluate enterprise sales platforms, including customer information management, online and offline collaboration, sales management, etc.
		Enterprise Information Portal	C2	Customer Relationship Management	C21	Evaluate the ability of seat companies to analyze customer data in an all-round way, achieve precise product marketing, and promote customer trust.

Table 2. *Cont.*

Competency Domain		Capability Subdomain		Evaluation Elements		Illustrate
Name	NO.	Name	NO.	Name	NO.	
Serve	D	Product Service	D1	Product Customization Service	D11	Evaluate the ability of enterprises to quickly provide customized products and services according to the individual needs of customers.
				Product Maintenance	D12	Evaluate the capabilities of enterprise product operation information management, predictive maintenance, etc.
		Customer Service	D2	Customer Personalized Service	D21	Evaluate the ability of chair industry enterprises to establish user interaction platform based on big data and realize intelligent customer service.
				After-sales Service	D22	Evaluate the ability of chair industry enterprises to provide timely statistics and feedback of customer information through the information system, guide product quality improvement evaluation, seat after-sales processing methods, claim settlement measures and other after-sales service behaviors, and maintain the ability to maintain customer relationships.

By analyzing and investigating the current situation of chair industry enterprises, the current production and operation modes of chair industry enterprises can be divided into independent design and manufacturing, Original Equipment Manufacturer (OEM), and parts manufacturing. The three types of enterprises have different focus areas of intelligent manufacturing. As shown in Figure 3, this study used the first type of enterprise as the research object.

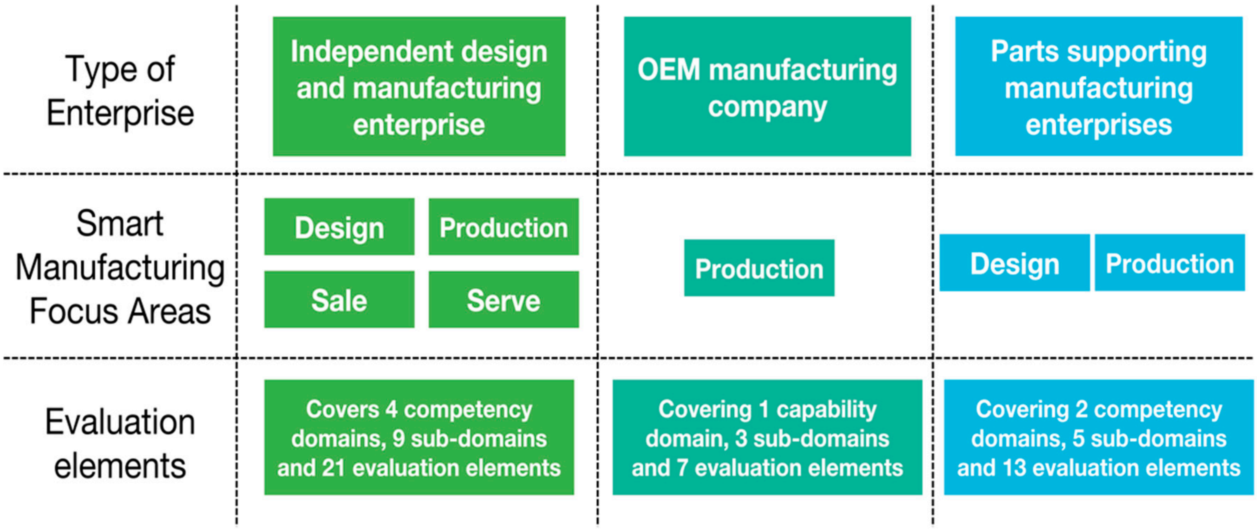


Figure 3. Focus areas of intelligent manufacturing of different types of chair industry enterprises.

4. Evaluation Model of Intelligent Manufacturing Capability Maturity of Chair Industry Enterprises

4.1. The Maturity of Intelligent Manufacturing Capabilities of Chair Industry Enterprises

The maturity of the evaluation index of intelligent manufacturing of chair industry enterprises refers to the ratio of the actual evaluation value of an index to the maturity value of the index. The value obtained after the three-level evaluation index maturity described in Table 2 is weighted and integrated; that is, the intelligent manufacturing maturity of the chair industry enterprise.

For the maturity weights of various indicators of intelligent manufacturing of chair industry enterprises, this study adopted the judgment matrix questioning method to design the questionnaire. By inviting experts in the industry to evaluate the relevance and importance of the evaluation indicators of the maturity of intelligent manufacturing capabilities of chair industry enterprises, 50 questionnaires were distributed to chair industry enterprises. Then, through the analysis of the correlation between the indicators in the questionnaire, the weights between the relevant indicators were determined. Through the weighted calculation of 21 indicators in the evaluation elements, the intelligent manufacturing capability maturity of nine indicators in the capability sub-domain could be obtained. In the same way, the maturity of the intelligent manufacturing capability of the four indicators in the capability domain can be obtained, and, finally, the maturity of the intelligent manufacturing capability of chair industry enterprises can be obtained.

4.2. Smart Manufacturing Capability Maturity Evaluation Process

4.2.1. Building the Network Structure

This study used ANP to evaluate the maturity of intelligent manufacturing capabilities of chair industry enterprises. ANP describes the relationship between the upper and lower levels within the evaluation system through the network structure. One goal and multiple criteria constitute the upper control layer, and multiple dominant elements constitute the lower network layer. The ANP model of intelligent manufacturing capability maturity of chair industry enterprises is shown in Figure 4.

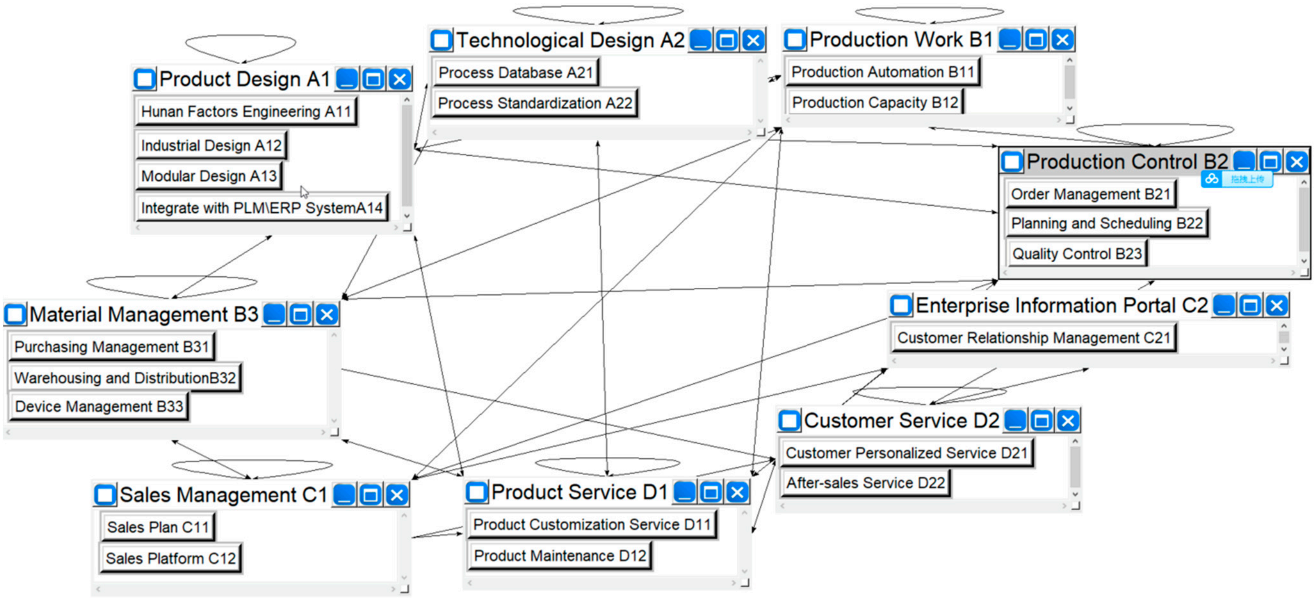


Figure 4. ANP evaluation model of intelligent manufacturing capability maturity of chair industry enterprises.

Due to the large amount of calculation involved in the use of ANP, this study used Super Decision software(SD, v2.10, William J. Adams, USA) to evaluate the model components. The element set and basic elements in ANP were, respectively, composed of the ability sub-domains and the indicators in the evaluation elements in Table 2; then the correlation between the evaluation indicators was obtained by analyzing the results of the questionnaire.

4.2.2. Indicator Weight Analysis

The ANP super-matrix is established from the constructed index relation network, and the matrix assigns the weight. The most important factor in this step is the comparison of the importance of each index. SD software provides five input modes for pairwise comparison, namely, questionnaire mode, graphic mode, text mode, matrix mode, and direct data entry [38–40]. This study adopted the questionnaire mode, organized according to the questionnaire results, and used the judgment matrix questioning method to input the data into the Super Decision software, as shown in Figure 5.

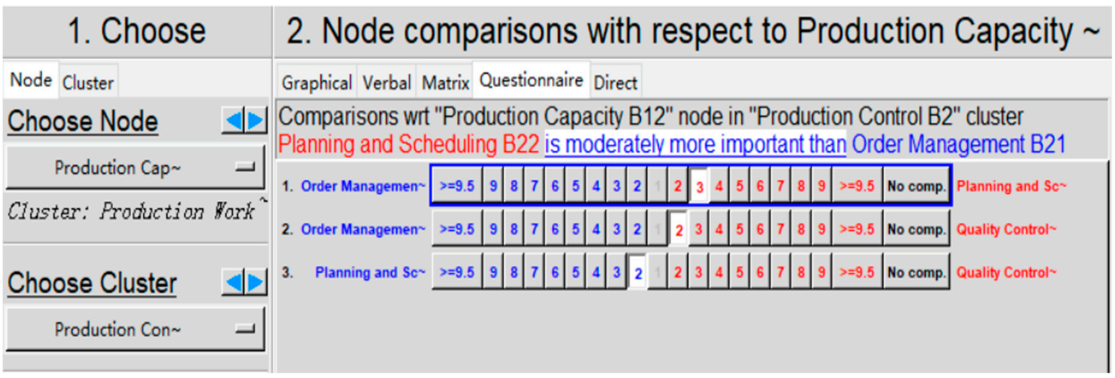


Figure 5. Comparison of elements under production automation criteria.

In the calculation process, the judgment matrix needs to be checked for consistency. When the judgment coefficients are all less than 0.1, it indicates that the weight is acceptable. The consistency check can be obtained in SD software, as shown in Figure 6.

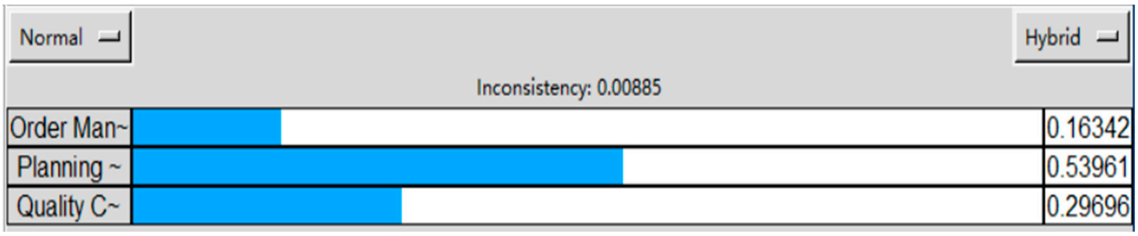


Figure 6. Index consistency test results.

A series of operations are performed based on the questionnaire data. The operation process is as follows:

1. Build an unweighted hypermatrix, as in Equation (1). The matrix W_{ij} represents the influence of the j element group on the i element group, and $\omega_{in}^{(jn)}$ represents the relative importance of the nth element of the i element group to the nth element of the j element group. The unweighted super matrix derived from SD software is shown in Figure 7.

$$W_{ij} = \begin{bmatrix} \omega_{i1}^{(j1)} & \omega_{i1}^{(j2)} & \dots & \omega_{i1}^{(jn)} \\ \omega_{i2}^{(j1)} & \omega_{i2}^{(j2)} & \dots & \omega_{i2}^{(jn)} \\ \vdots & \vdots & \dots & \vdots \\ \omega_{in}^{(j1)} & \omega_{in}^{(j2)} & \dots & \omega_{in}^{(jn)} \end{bmatrix} \quad (1)$$

Cluster Node Labels		Customer Service D2		Enterprise Information Portal C2	Material Management B3			Product Design A1	
		After-sales Service D22	Customer Personalized Service D21	Customer Relationship Management C21	Device Management B33	Purchasing Management B31	Warehousing and DistributionB32	Hunan Factors Engineering A11	Industrial Design A12
Customer Service D2	After-sales Service D22	0.000000	1.000000	0.000000	0.000000	0.000000	0.666667	0.000000	0.000000
	Customer Personalized Service D21	1.000000	0.000000	1.000000	0.000000	0.000000	0.333333	0.000000	0.000000
Enterprise Information Portal C2	Customer Relationship Management C21	1.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Material Management B3	Device Management B33	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	Purchasing Management B31	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	1.000000	1.000000
	Warehousing and DistributionB32	0.000000	0.000000	0.000000	1.000000	1.000000	0.000000	0.000000	0.000000
Product Design A1	Hunan Factors Engineering A11	0.527836	0.310814	0.000000	0.000000	0.000000	0.000000	0.000000	0.614411
	Industrial Design A12	0.332516	0.195800	0.000000	0.000000	0.000000	0.000000	0.673811	0.000000

Figure 7. Unweighted hypermatrix (partial data) exported by SD software.

2. Build a weighting matrix. In the formula, b_{NN} is a sorting vector obtained by comparing the importance of the N elements of the capability subfield to the evaluation indicators.

$$A = \begin{bmatrix} b_{11} & \cdots & b_{1N} \\ \vdots & \ddots & \vdots \\ b_{N1} & \dots & b_{NN} \end{bmatrix} \quad (2)$$

3. Equations (1) and (2) are multiplied, that is, the weighted matrix A and the matrix W_{ij} are multiplied to obtain the weighted supermatrix $\overline{W_{ij}}$. The weighted super matrix derived from SD software is shown in Figure 8.

Cluster Node Labels		Customer Service D2		Enterprise Information Portal C2	Material Management B3			Product Design A1	
		After-sales Service D22	Customer Personalized Service D21	Customer Relationship Management C21	Device Management B33	Purchasing Management B31	Warehousing and DistributionB32	Hunan Factors Engineering A11	Industrial Design A12
Customer Service D2	After-sales Service D22	0.000000	0.250000	0.000000	0.000000	0.000000	0.111111	0.000000	0.000000
	Customer Personalized Service D21	0.250000	0.000000	0.333333	0.000000	0.000000	0.055556	0.000000	0.000000
Enterprise Information Portal C2	Customer Relationship Management C21	0.250000	0.250000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Material Management B3	Device Management B33	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	Purchasing Management B31	0.000000	0.000000	0.000000	0.000000	0.000000	0.166667	0.200000	0.200000
	Warehousing and DistributionB32	0.000000	0.000000	0.000000	0.250000	0.333333	0.000000	0.000000	0.000000
Product Design A1	Hunan Factors Engineering A11	0.131959	0.077703	0.000000	0.000000	0.000000	0.000000	0.000000	0.122882
	Industrial Design A12	0.083129	0.048950	0.000000	0.000000	0.000000	0.000000	0.134762	0.000000

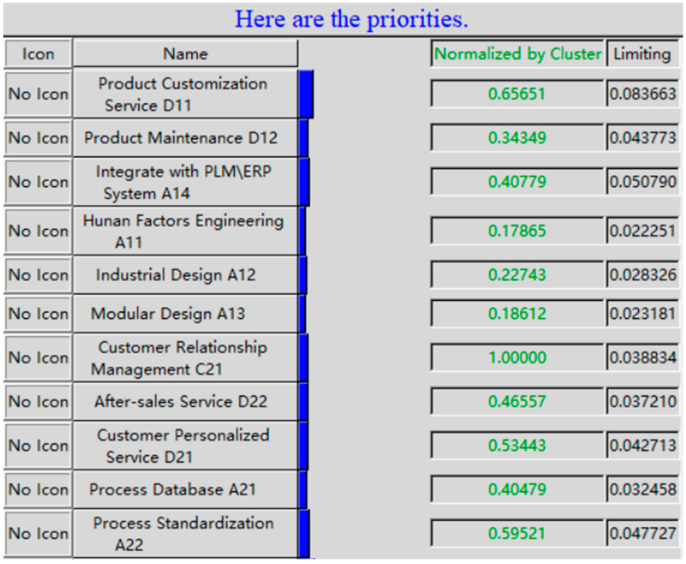
Figure 8. Weighted hypermatrix derived from SD software (partial data).

4. Limiting the weighted super-matrix, the value of each column after limiting is the weight of the corresponding index, and the limiting weighted super-matrix is derived from SD software, as shown in Figure 9.

Cluster Node Labels		Customer Service D2		Enterprise Information Portal C2	Material Management B3			Product Design A1	
		After-sales Service D22	Customer Personalized Service D21	Customer Relationship Management C21	Device Management B33	Purchasing Management B31	Warehousing and DistributionB32	Hunan Factors Engineering A11	Industrial Design A12
Customer Service D2	After-sales Service D22	0.037210	0.037210	0.037210	0.037210	0.037210	0.037210	0.037210	0.037210
	Customer Personalized Service D21	0.042713	0.042713	0.042713	0.042713	0.042713	0.042713	0.042713	0.042713
Enterprise Information Portal C2	Customer Relationship Management C21	0.038834	0.038834	0.038834	0.038834	0.038834	0.038834	0.038834	0.038834
Material Management B3	Device Management B33	0.034247	0.034247	0.034247	0.034247	0.034247	0.034247	0.034247	0.034247
	Purchasing Management B31	0.057865	0.057865	0.057865	0.057865	0.057865	0.057865	0.057865	0.057865
	Warehousing and DistributionB32	0.091793	0.091793	0.091793	0.091793	0.091793	0.091793	0.091793	0.091793
Product Design A1	Hunan Factors Engineering A11	0.022251	0.022251	0.022251	0.022251	0.022251	0.022251	0.022251	0.022251
	Industrial Design A12	0.028326	0.028326	0.028326	0.028326	0.028326	0.028326	0.028326	0.028326

Figure 9. Limiting weighted hypermatrix derived from SD software (partial data).

5. Calculate the local weight and global weight of the chair industry enterprise evaluation index, as shown in Figure 10. The left side of the result column in the figure is the local weight, and the right side is the global weight.



Here are the priorities.

Icon	Name	Normalized by Cluster	Limiting
No Icon	Product Customization Service D11	0.65651	0.083663
No Icon	Product Maintenance D12	0.34349	0.043773
No Icon	Integrate with PLM\ERP System A14	0.40779	0.050790
No Icon	Hunan Factors Engineering A11	0.17865	0.022251
No Icon	Industrial Design A12	0.22743	0.028326
No Icon	Modular Design A13	0.18612	0.023181
No Icon	Customer Relationship Management C21	1.00000	0.038834
No Icon	After-sales Service D22	0.46557	0.037210
No Icon	Customer Personalized Service D21	0.53443	0.042713
No Icon	Process Database A21	0.40479	0.032458
No Icon	Process Standardization A22	0.59521	0.047727

Figure 10. Global indicator weights of chair industry enterprises (partial data).

4.2.3. Weight Calculation Result

The weight values of each index can be obtained from the above analysis and calculation process, as shown in Table 3.

Table 3. The weight of the maturity index of intelligent manufacturing capability of chair industry enterprises.

Content	Weight Vector
Capability Domain Indicator Weight	0.204733; 0.452965; 0.134945; 0.153681
Capability sub-domain indicator weight	0.124548; 0.080185; 0.084515; 0.184545; 0.183905; 0.096111; 0.038834; 0.127436; 0.079923
The weight of each indicator under the capability sub-domain indicator A1	0.022251; 0.028326; 0.023181; 0.050790
The weight of each indicator under the capability sub-domain indicator A2	0.032458; 0.047727
The weight of each indicator under the capability sub-domain indicator B1	0.017343; 0.067172
The weight of each indicator under the capability sub-domain indicator B2	0.065989; 0.098095; 0.020461
The weight of each indicator under the capability sub-domain indicator B3	0.057865; 0.091793; 0.034247
The weight of each indicator under the capability sub-domain indicator C1	0.054137; 0.041974
The weight of each indicator under the capability sub-domain indicator C2	0.038834
The weight of each indicator under the capability sub-domain indicator D1	0.083663; 0.043773
The weight of each indicator under the capability sub-domain indicator D2	0.042713; 0.037210

It can be seen from the above calculation results that the local weights of chair industry enterprises are relatively balanced, in which the design index weight is 0.204733, the production index weight is 0.452965, the sales index weight is 0.134945, and the service index weight is 0.153681. The weights of various indicators in the above table also reflect chair industry enterprises' production and operation status.

5. Maturity Assessment of Intelligent Manufacturing Capabilities of 50 Chair Industry Companies

The government entrusted the Anji Intelligent Manufacturing Technology Research Institute of Hangzhou Dianzi University to conduct an intelligent manufacturing capability diagnosis for the chair industry. After a two-month field survey and interviews with company leaders, the Anji Intelligent Manufacturing Technology Research Institute of Hangzhou Dianzi University evaluated and diagnosed the intelligent manufacturing capabilities of 50 chair industry enterprises. According to the evaluation indicators, a scoring data set of 50 companies was formed. Based on the overall maturity evaluation process of intelligent manufacturing of chair industry enterprises, 50 self-produced manufacturing enterprises were selected, and the overall maturity of intelligent manufacturing of these 50 chair industry enterprises was evaluated. According to the five-point scoring standard, the minimum score for enterprises that have not yet begun to implement intelligent manufacturing construction is 0 points, and the maximum score for enterprises that have completed intelligent manufacturing construction is 5 points. The evaluation results obtained by these 50 enterprises after evaluation according to this standard were compared with the evaluation results using the general intelligent manufacturing maturity evaluation model (Chinese national standard). The rating results of the 50 companies are shown in Figure 11. As shown in the figure, two companies have reached the optimization level, seven have reached the integration level, 17 have reached the standard level, and 24 have reached the planning level. Figure 12 shows a comparison of the evaluation metrics for a company selected from each of the four levels achieved. It can be seen from the figure that AJ8 is already at a high level of intelligence.

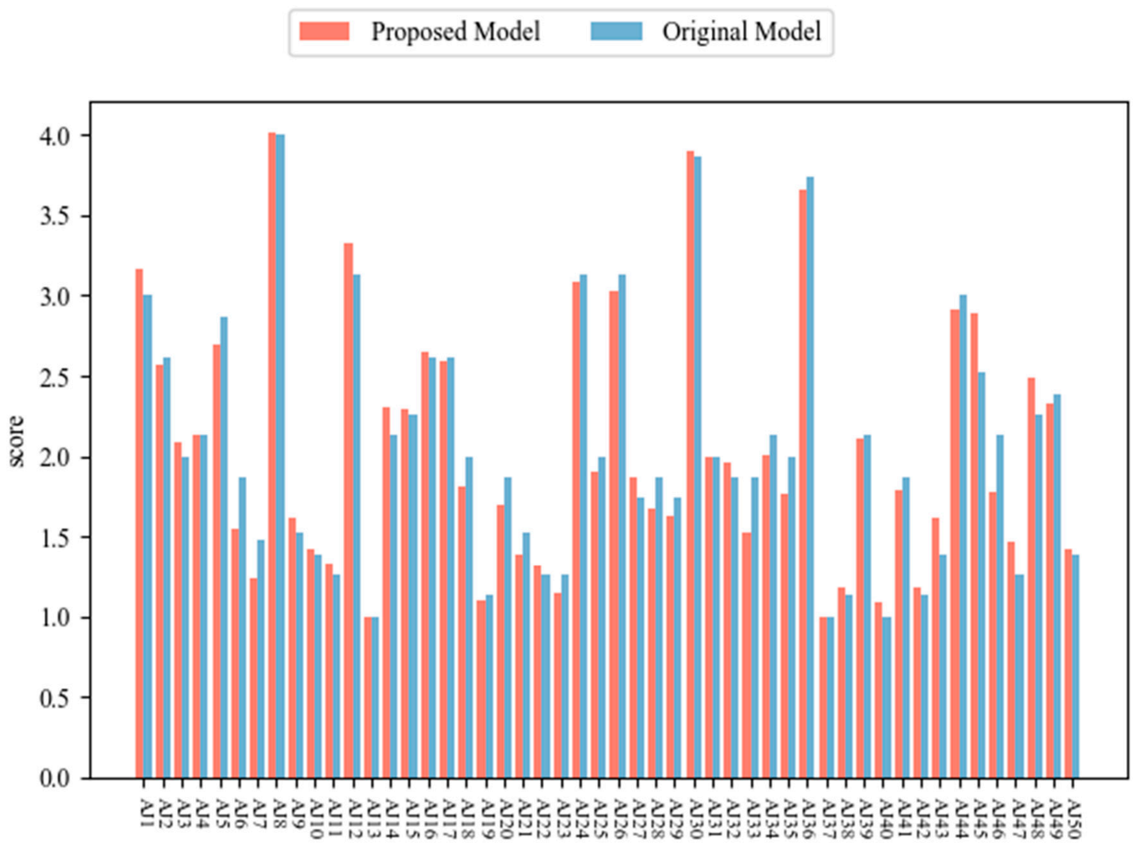


Figure 11. Comparison of evaluation results of different models.

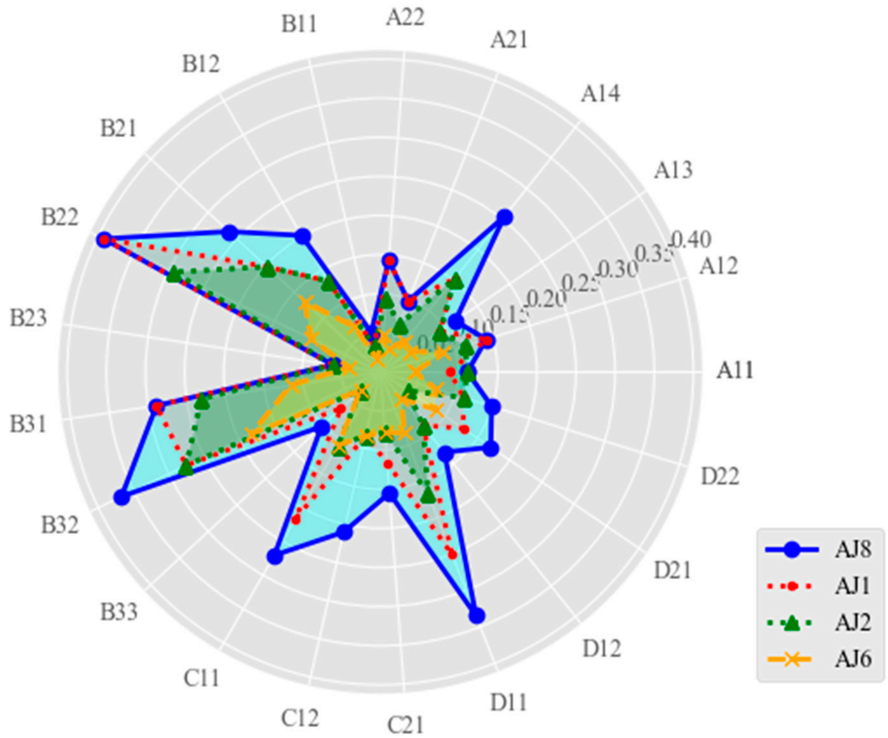


Figure 12. Comparison of evaluation indicators of chair industry enterprises (partial data).

The general intelligent manufacturing maturity evaluation model (Chinese national standard) and the research model of this paper were used to evaluate 50 enterprises. Table 4 shows the comparison of the evaluation results of some enterprises. The results show that two companies were evaluated as being at the optimized level by the two evaluation models, but their evaluation scores according to the model proposed in this paper are higher than those evaluated by the general intelligent manufacturing maturity evaluation model (Chinese national standard). In addition, one company was downgraded from the integration level to the normative level, seven companies were downgraded from the normative level to the planning level, and one company was raised from the planning level to the normative level. The evaluation results of each enterprise show that, compared with the general evaluation model of the Chinese national standard, the results obtained using the research model in this paper can more accurately reflect the current status of the intelligent manufacturing level of chair industry enterprises.

Table 4. Comparative analysis of evaluation results of different models (part of enterprises).

Chair Industry	National Standard Evaluation Model		Proposed Model	
	Overall Ratings	Level	Overall Ratings	Level
AJ8	4	Optimized level	4.02	Optimized level
AJ30	3.87	Optimized level	3.90	Optimized level
AJ5	2.87	Integration level	2.70	Normative level
AJ6	1.87	Normative level	1.55	Planning level
AJ20	1.87	Normative level	1.70	Planning level
AJ28	1.87	Normative level	1.67	Planning level
AJ33	1.87	Normative level	1.53	Planning level
AJ35	2	Normative level	1.77	Planning level
AJ41	1.87	Normative level	1.79	Planning level
AJ46	2.13	Normative level	1.78	Planning level
AJ27	1.74	Planning level	1.87	Normative level

6. Conclusions

In view of the development status of various chair industry enterprises and the level of intelligent manufacturing technology, and combined with China's national standards, this study established a multi-level evaluation element system to assess the maturity of intelligent manufacturing of chair industry enterprises, and built an evaluation model of intelligent manufacturing maturity for chair industry enterprises. Using ANP and SD software, a multi-objective and multi-attribute comprehensive evaluation model was established, which can more objectively reflect the complex relationship between evaluation indicators in the development level of intelligent manufacturing in chair industry enterprises. Compared with the general model released by the Standardization Administration of China, the model in this paper can more accurately evaluate the development of intelligent manufacturing in chair enterprises. The calculation results of the evaluation model in this paper can show the current level of intelligent manufacturing capabilities of enterprises, and can accurately reflect the overall development status of intelligent manufacturing in chair industry enterprises and the construction level of individual indicators. These findings can help chair industry enterprises to quickly identify their own shortcomings, and according to the needs of enterprises, improve the digital construction and intelligent construction of enterprises in a targeted manner. The research in this study mainly focused on the Chinese chair industry, and can provide a reference for the intelligent transformation of the chair industry in other countries. As a result, this will further improve the proposed model in future research by adding more countries' chair industry data.

Author Contributions: Conceptualization, W.W. and J.W.; methodology, S.S. and J.W.; software, W.W. and J.W.; validation, W.W., J.W. and C.C. (Chang Chen); formal analysis, C.C. (Chang Chen); investigation, W.W., C.C. (Chang Chen), S.S., C.C. (Changyong Chu) and G.C.; resources, W.W., C.C. (Chang Chen) and S.S.; data curation, W.W. and J.W.; writing—original draft preparation, W.W., J.W. and S.S.; writing—review and editing, W.W. and J.W.; visualization, J.W. and C.C. (Changyong Chu); supervision, C.C. (Changyong Chu) and G.C.; project administration, S.S. and G.C.; funding acquisition, S.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Key R & D plan of Zhejiang Province, application and demonstration of "intelligent generation" technology for small and medium-sized enterprises—R & D and demonstration application of chair industry internet innovation service platform based on Artificial Intelligence, grant number 2020C01061.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: The author would like to thank the companies involved in this article and their engineers for their help with the data required for this article.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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