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Research on the Correlation between Industry 4.0 and Sustainable Development in the Machine Tool industry – Application of QFD and Fuzzy MADM methods

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Abstract

Starting in 2025, Taiwan will introduce a requirement that listed companies with a paid-in capital of less than 2 billion NTD need to prepare a sustainability report. Most of the actual income scale of Taiwan's machine tool industry falls within this range. In response to the requirement, the machine tool industry must reduce its impact on the environment and society and strike a balance while increasing economic returns. This is undoubtedly a major challenge for the machine tool industry, which is one of the most internationally competitive industries in Taiwan. If sustainable development (SD) can be successfully implemented, it will set a benchmark for Taiwan's traditional industries.

The machine tool industry has continued to improve its industrial competitiveness in recent years, especially after Germany proposed the concept of Industry 4.0 in 2013, which accelerated the pace of industrial upgrading and transformation. Studies have shown that the adoption of Industry 4.0 technology can effectively enhance the sustainable performance of enterprises. Additionally, in the literature on SD, it has been confirmed that there is a significant positive relationship between corporate social responsibility and profitability.

This study will propose a reasonable and feasible model framework to demonstrate the relationship between SD factors and Industry 4.0 technical indicators, aiming to identify the key Industry 4.0 technologies to improve

SD. This study uses the Quality Function Deployment (QFD) method as the basic structure and adopts the Fuzzy Delphi Method (FDM) of the Multiple Attribute Decision Making (MADM), the improved Fuzzy Extended Analytic Hierarchy Process (FEAHP), and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for prioritizing performance index factors.

Keywords: *Machine Tool Industry, Industry 4.0, Sustainable Development, Quality Function Deployment, Multiple Attribute Decision Making*

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1. Introduction

1.1 Research Background

Garbie (2015) emphasized that corporate sustainability goals are multidimensional and challenging to define. These goals must be broken down into various departments and business areas for effective promotion. In the process of achieving this goal, companies must invest considerable efforts in achieving effective communication and optimizing value strategies (Hansen & Schaltegger, 2016). Silvestre & Ţîrcă (2019) pointed out that without innovation, a company cannot achieve sustainable performance. The innovation in enterprises is undoubtedly related to technological advancements. Many studies have shown that since Germany proposed the fourth industrial revolution (also known as Industry 4.0) in 2013, it has provided innovative tools to assist enterprises in technological transformation (Lopes de Sousa Jabbou et al., 2018; Nara et al., 2021). As enterprises strengthen their competitive advantages and undergo technological transformation, they must consider their responsibilities to the environment (Handfield et al., 2001) and to society in their manufacturing practices as sustainability issues arise. It is a big challenge for enterprises, but the challenge is the turning point. Helleno et al. (2017) pointed out that achieving a balance between the economic, social, and environmental levels brings many benefits to enterprises.

Sustainable Development (SD) is defined as the enterprise reducing and balancing its impact on the environment and society while increasing economic returns (Helleno et al., 2017). Moreover, the impact on the environment from its production process and finished products must be minimized (Stock & Seliger, 2016). Jamaludin et al. (2013) also emphasized that when managing corporate sustainability, one must be aware of the economic, social, and environmental impacts. Therefore, the sustainability perspective is often referred to as the Triple Bottom Line (TBL), covering three aspects: environmental, social, and economic (Barber et al., 2012; Chang & Cheng, 2019; Hsu et al., 2017; Seuring & Muller, 2008).

Bonn & Fisher (2011) suggested that in the strategic decision-making process, managers need to combine different factors with various sustainability measures so that companies can identify opportunities for sustainability improvements. However, Sharma et al. (2020) pointed out that if companies can effectively implement Industry 4.0 technology, it is entirely possible to achieve a win-win situation at the three levels of economy, society, and environment. Therefore, the impact of Industry 4.0 on SD has received increasing attention from scholars (Ghobakhloo, 2020). While the environmental and economic impacts of smart manufacturing have been studied (Gu et al., 2019), further research is needed on the impact of practices on sustainability (Ford & Despeisse, 2016; Müller et al., 2018).

This study chooses the machine tool industry as the object of research and demonstration. The reason is that the machine tool industry can be regarded as an indicator of a country's industrialization level. Moreover, the supply chain system of the machine tool industry is comprehensive, with the number of suppliers ranging from dozens to hundreds. Faced with such a large total, the machine tool industry is a major target for promoting sustainability. The research conclusions obtained will better reflect the current status of Taiwan's machine tool industry in SD.

1.2 Research Purpose

The growth of the manufacturing industry is crucial for a country's economic development. The manufacturing industry is facing an important challenge: balancing the economic development needs of organization with environmental protection and social responsibility (Burke & Gaughran, 2007; Diab et al., 2015; Shultz & Holbrook, 1999). Numerous recent studies have emphasized that economic development cannot overlook the significance of SD. Taiwan, a former model of economic development in Asia, and its machine tool industry, which once ranked among the top five machine tool manufacturers in the world (Yeh & Chang, 2003), need to align with the current international trend of pursuing sustainability. Bonn & Fisher (2011) pointed out that the SD of enterprises covers quite complex content and therefore requires comprehensive strategic considerations at different organizational levels. However, in reality, there is a significant difference between manufacturing and SD. Addressing how to develop an industry that considers environmental protection, social fairness, justice, economic efficiency, and strikes a balance to prevent the continued expansion of gaps while building a suitable environment for industrial development is a significant challenge. Adopting a sustainable business model is a necessary development path.

The implementation of SD in industry is a necessary choice for humans to achieve Sustainable Manufacturing (SM). However, implementing SD is not easy, it is more difficult, especially in developing and underdeveloped countries. Faced with this serious issue, this study proposes a novel structural model to solve the above problems, demonstrates the relationship between SD factors and Industry 4.0 technical indicators, and thereby finds key Industry 4.0 technologies to improve SD. To sum up, how to assist the machine tool industry in finding key Industry 4.0 performance indicators is the topic of this study.

The study combines Industry 4.0 technology with SD factors, formulates a key performance indicator structure through Quality Function Deployment (QFD), and employs the FDM of MADM, FEAHP, TOPSIS to identify key Industry 4.0 technical indicators. Next, prioritize and reveal potential ways in which key performance indicators can enhance the sustainability of Taiwan's machine tool industry. The method proposed in this study can also be used in different companies or industries. This is the original value of this study.

2. Literature Review and Discussion

2.1 Quality Function Deployment Literature Review

QFD was developed by Japanese scholars Yoji Akao and Shigeru Mizuno in the 1960s. The primary function of QFD is to convert customer demands into appropriate technology requirements during the phases of product development and manufacturing (Sullivan, 1986).

In recent years, QFD, synthesized from various theories, has found widespread application across diverse fields. For instance, Vinodh and Chintha (2011) integrated QFD with fuzzy theory, effectively assisting enterprises in defining a sustainable competitive basis, scope, and key factors. Chang (2012) employed the interplay between supply and demand to apply QFD in analyzing the uncertainty and flexibility of manufacturing systems. Anwar et al. (2013) utilized the QFD structure to delineate customers' needs, thereby enhancing the service quality of cafes. Büyüközka and Çifçi (2013) used QFD as a tool to improve product or system planning. Zaim et al. (2014) integrated QFD with FANP to explore product development. Lin et al. (2015) also applied QFD to improve the service process of Taiwanese banquet culture. Hsu et al. (2017) utilized QFD to identify key performance factors for SMEs, thereby promoting SD.

2.2 Sustainable Development

Environmental damage and climate change pose a serious threat to the future survival of human beings, eliciting great concern among academics, practitioners, and government units (Shove et al., 2015). Various international conventions emphasize the need to protect environmental resources and reduce the challenges of industrial environmental pollution through diverse means. In addition, governments worldwide are formulating stricter laws and regulations to restrict environmental pollution problems (Wang et al., 2016). SD was initially introduced in the "World Conservation Program" by the "International Union for the Conservation of Nature and Natural Resources" in 1980. Later, in 1987, the World Commission on Environment and Development (WCED) proposed a definition of SD: it can meet the needs of the present without compromising the ability of future generations to meet their own needs (Chang & Cheng, 2019; Helleno et al., 2017; WCED, 1987). Tanguay et al. (2010) identified three major aspects of SD: economy, society, and environment. For SD to be realized, it must be based on fairness and reasonableness (overlap of economy and society), appropriateness for survival (overlap of society and environment), and feasibility (overlap of environment and economy), as shown in Figure 1.

People have gradually realized that sustainability is one of the advantages of future competition; therefore, investment in SD is increasing in all industries (Hopkins et al., 2011). In the SD literature, it has been confirmed that there is a significant positive relationship between corporate social responsiveness and profitability (Waddock & Graves, 1997; Margolis & Walsh, 2001; Ciliberti et al., 2008). Stocchetti (2012) pointed out that both academia and industry are emphasizing that improving SM and performance is an opportunity for corporate development and growth. The benefits of improving sustainability can enhance corporate image and reputation (Lee, 2012).

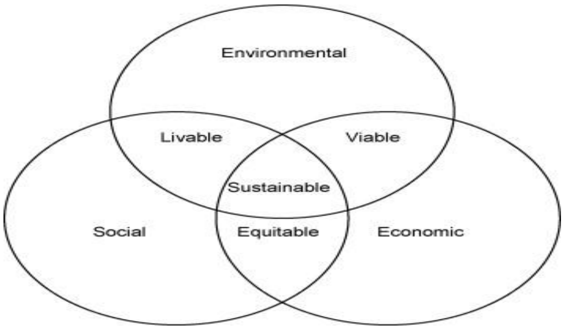


Figure 1.
Classic dimensions of sustainable development.
Resources: Tanguay et al. (2010)

2.3 Literature Review on SD Indicators and Factors

In the realm of sustainability literature, SD has become the most discussed topic in the 21st century (Di Fabio & Peiró, 2018; Sen, 2014). Currently, the SD Triple Bottom Line (TBL) perspective, introduced by Elkington (1997), serve as the primary framework for measurement adopted by most scholars. However, alternative indicator factors have been proposed by scholars based on empirical industries or unique perspectives (Hsu et al., 2017). To meet the needs of practical applications and assist the machine tool industry in carrying out sustainable operations, this study summarizes relevant and appropriate economic, social, and environmental SD indicator factors through a literature review. Table 1 is a literature collection of SD indicator factors in the economic aspect. Table 2 is a literature collection on SD indicator factors in the social aspect, and Table 3 is a literature collection on the SD indicator factors of the environmental aspect.

2.4 Literature Review of Industry 4.0 Technical Indicators

Nowadays, Industry 4.0 is ushering in a new revolution worldwide. The term 'Industry 4.0' signifies the 4th industrial revolution, a concept introduced by the federal government of Germany in 2011 (Upadhyay et al. 2021). This revolution encompasses advanced manufacturing techniques and information technologies that converge to create smart systems (Wei et al., 2017). Manufacturing systems are now undergoing transformative changes in operations, design, product services, and production systems. This illustrates how industry 4.0 is introducing novel and intelligent advancements. (Rüßmann et al., 2015). The entire industrial chain is embracing a new technological and future-oriented perspective with the aim of enhancing effectiveness and efficiency (Lu, 2017; Dalenogare et al., 2018). Fundamentally, Industry 4.0 is rooted in the emergence of new technologies, including additive

Table 1
Literature collection of SD indicator factors in the economic aspect

Dimension	Objective	Indicator Factors	References								
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Economy	Cost reduction	Reduce manufacturing costs.	●	●		●	●	●	●	●	●
		Reduce procurement costs.	●	●	●	●		●	●	●	●
		Reduce distribution costs.		●	●	●	●	●	●	●	●
	Quality improvement	Enhance service quality.			●	●				●	
		Enhance product quality.		●	●	●		●	●	●	●
	Delivery performance	Enhance proportion of on-time delivery.				●	●	●	●	●	●
		Reduce transport time.			●		●		●	●	
	Economic potential	Enhance the degree of enterprise innovation.	●		●	●			●	●	●
		Improve manufacturing technology.	●			●		●		●	●

(1) Baumgartner & Rauter (2017); (2) Zhan et al. (2018); (3) Cantele & Zardini (2018); (4) Caiado et al. (2017); (5) Singh et al. (2016) ;(6) Chang & Cheng (2019) ;(7) Amrina & Yusof (2011); (8) Govindan et al. (2013); (9) Govindan et al. (2016).

Table 2
Literature collection of SD indicator factors in the social aspect

Dimension	Objective	Indicator Factors	References							
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Society	Community impact	Reduce the degree of community health effects.			●			●	●	●
		Support community development plans.	●		●		●			
		Support educational institutions.	●				●			
		Feedback of local communities	●					●		●
		Increase employment opportunities in local communities	●				●	●		●
	Work environment	Reduce the incidence of health and safety problems in the enterprise.	●	●			●		●	●
		Reduce the incidence of discrimination cases.			●			●		●
		Senior management's commitment to SD		●	●	●	●	●		
		Assist employees to develop second expertise	●	●					●	●
		Reduce staff turnover			●	●	●	●		
	Customer relationship	Enhance the safety and health of customers in using products.			●		●			●
		Increase the channels of product information to customers.	●		●		●			●
		Zero customer complaints and returns			●	●	●	●		
		Green image			●	●		●		

(1) Baumgartner & Rauter (2017); (2) Zhan et al. (2018); (3) Cantele & Zardini (2018); (4) Caiado et al. (2017); (5) Singh et al. (2016); (6) Chang & Cheng (2019); (7) Amrina & Yusof (2011); (8) Govindan et al. (2013).

Table 3
Literature collection of SD indicator factors in the environmental aspect

Dimension	Objective	Indicator Factors	References								
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Environment	Substance Emissions	Reduce the amount of harmful substances produced.	●	●				●	●		
		Noise disturbance			●						
		Reduce the degree of water pollution.	●	●			●		●	●	
		Reduce the degree of land pollution.	●	●			●		●		
		Reduce the degree of air pollution.	●	●					●		
		Reduce greenhouse gas emissions (methane, CO_2)		●		●					
	Resource consumption	Reduce land usage.					●				
		Reduce water usage.		●					●	●	
		Reduce energy usage.		●		●			●		
		Reduce the risk of product dumping	●					●			
	Green manufacturing	Develop products that are recyclable.						●			●
		Products developed for recycling waste						●			●
		Increase the use of green energy							●		
		Design green products						●			●
		Use green factory buildings				●					
		Green Supply Chain									●
	Environmental policy	Obtain the relevant environmental certifications.			●	●					
		Strengthen publicity on environmental protection	●		●		●				
		Strengthen the natural resources or environmental protection actions.					●		●		

(1) Alcamo (2019); (2) de Oliveira et al. (2019); (3) Alquezar & Macedo (2019); (4) Asif (2016); (5) Fang et al. (2019); (6) Russo et al. (2019); (7) Amrina & Yusof (2011); (8) Vanham et al. (2018); (9) D'Amore et al. (2017).

manufacturing, cloud computing, the Internet of Things (IoT), Cyber-Physical Systems (CPS), sensor technology, 3D printers, internet of thinking technology, artificial intelligence, and big data (Ghobakhloo, 2018; Goodell et al. 2021; Jabeen et al. 2019; Moeuf et al., 2018; Mittal et al., 2019; Roy & Roy 2019).

Improved control of operations, allowing for real-time adaptation and flexibility depending on demands, can be provided by these technologies. These ideas are also capable of generating small, customized production batches (Rüßmann et al., 2015; Zhong et al., 2017). The crucial features of these technologies include the creation of smart systems at the factory level, providing better energy consumption efficiency, and consequently, having a positive environmental impact (Dalenogare et al., 2018). Therefore, these systems have the ability not only to assist companies in achieving Circular Economies (CE) but also to pursue brand-new, eco-friendly, and environmentally-friendly strategies for product development. (de Sousa Jabbour et al., 2018; Tseng et al., 2018). In other words, Industry 4.0 technologies encourage and promote SD by influencing industrial systems, environmental resources, and wider society, both for the present and future generations. (Ghobakhloo, 2018). Lastly, an analysis and closer examination of the impact of Industry 4.0 technologies from a sustainability perspective, considering economic, environmental, and social aspects, was conducted with thorough thought. The study concluded relevant and suitable Industry 4.0 technology indicators through a literature review, as shown in Table 4.

Table 4
Literature collection table of Industry 4.0 technical indicators

Dimension	Technology Indicators	References									
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Management	Cyber-Physical System.		●	●		●	●		●	●	●
	Lean Production.			●						●	
	Product Lifecycle Management.			●				●	●		
	Smart Manufacturing.				●	●	●		●	●	
Application	Manufacturing Execution System.	●			●						
	Enterprise Resource Planning.		●		●						
	Business Intelligence.		●								
	Industrial Internet of Things (IIOT).						●				●
	Integrated Engineering Systems.	●					●				
	Big Data.	●	●		●	●				●	●
	Digital Product-Service Systems.	●									
	Cloud Computing.		●		●		●			●	●
	Cloud Services for Products (CLOUD).	●					●				●
Internet	Data Mining.				●				●		
	Network Security.		●				●			●	
	Smart Product /Intelligent Product.		●	●	●		●			●	
	Smart Electric Grid/Intelligent Grid.		●					●	●		
	Information and Communications Technology.		●	●	●		●		●	●	

(1) Dalenogare et al. (2018)； (2) Lu (2017)； (3) Mrugalska & Wyrwicka (2017)； (4) Frank et al. (2019)； (5) Masood & Egger (2019)； (6) Boyes et al. (2018)； (7) Faheem & Gungor (2018)； (8) Stock & Seliger (2016)；(9) Kamble et al. (2018)； (10) Ivanov et al. (2019).

Table 4
Literature collection table of Industry 4.0 technical indicators (continuous)

Dimension	Technology Indicators	References									
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Perception	Digital automation with sensors.	●			●				●	●	●
	Simulation and analysis of network.	●		●	●			●			●
	Radio-Frequency identification (RFid).		●	●		●			●	●	
	Wireless Sensor Network.						●	●		●	
	Embedded System.		●				●	●			
Equipment	Robot Operating System.				●					●	●
	Automation.			●	●		●			●	●
	Supervisory Control and Data Acquisition (SCADA).	●	●		●	●	●				
	Flexible Manufacturing Lines.	●			●						
	Augmented Reality (AR).			●		●				●	
	Simulations/Analysis of Virtual Models.			●		●				●	●
	Additive Manufacturing, Fast Prototyping or 3D impression.	●			●	●				●	●
	Prototype Design.		●					●		●	
	Automation Guided Vehicle (AGV).						●		●		
	Computer-Aided Design and Manufacturing (CAD/CAM).	●								●	

(1) Dalenogare et al. (2018)；(2) Lu (2017)；(3) Mrugalska & Wyrwicka (2017)；(4) Frank et al. (2019)；(5) Masood & Egger (2019)；(6) Boyes et al. (2018)；(7) Faheem & Gungor (2018)；(8) Stock & Seliger (2016)；(9) Kamble et al. (2018)；(10) Ivanov et al. (2019).

3. Methodology and steps

The methods employed and operational steps are organized as follows. Firstly, this study used the fuzzy Delphi method (FDM) to select important SD criteria and Industry 4.0 performance indicators. Secondly, we used a modified fuzzy extent analytical hierarchy process (FEAHP) to evaluate the weighted importance of SD criteria, and the fuzzy theory measures the correlations among the performance indicators and the relations between SD criteria and performance indicators. Finally, this study used the technique for order preference by similarity to ideal solution method (TOPSIS) to prioritize performance indicators.

A schematic illustration and steps of the proposed approaches for prioritizing the performance indicators is shown in Figure. 2.

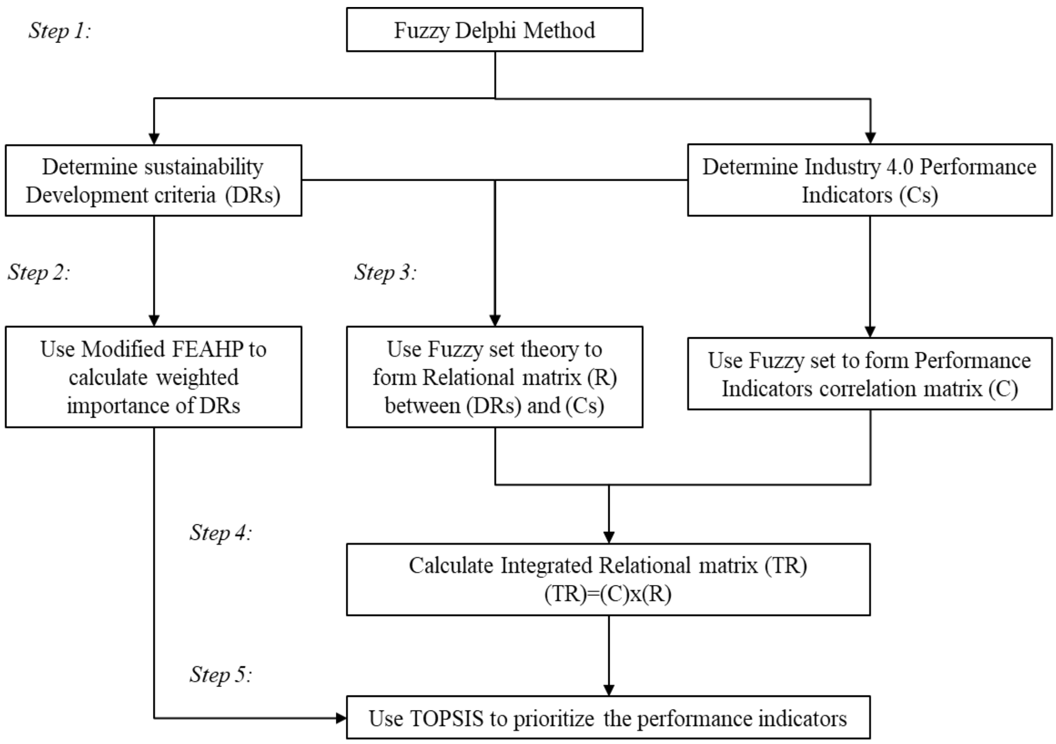


Figure 2
The scheme of the proposed approaches

3.1 Quality function deployment

Quality function deployment uses a series of associated matrices to construct a house of quality as the development structure. This study is referred to as the house of quality used by Anwar et al. (2013), who expanded upon it. The main structure (Figure. 3) and steps are as follows:

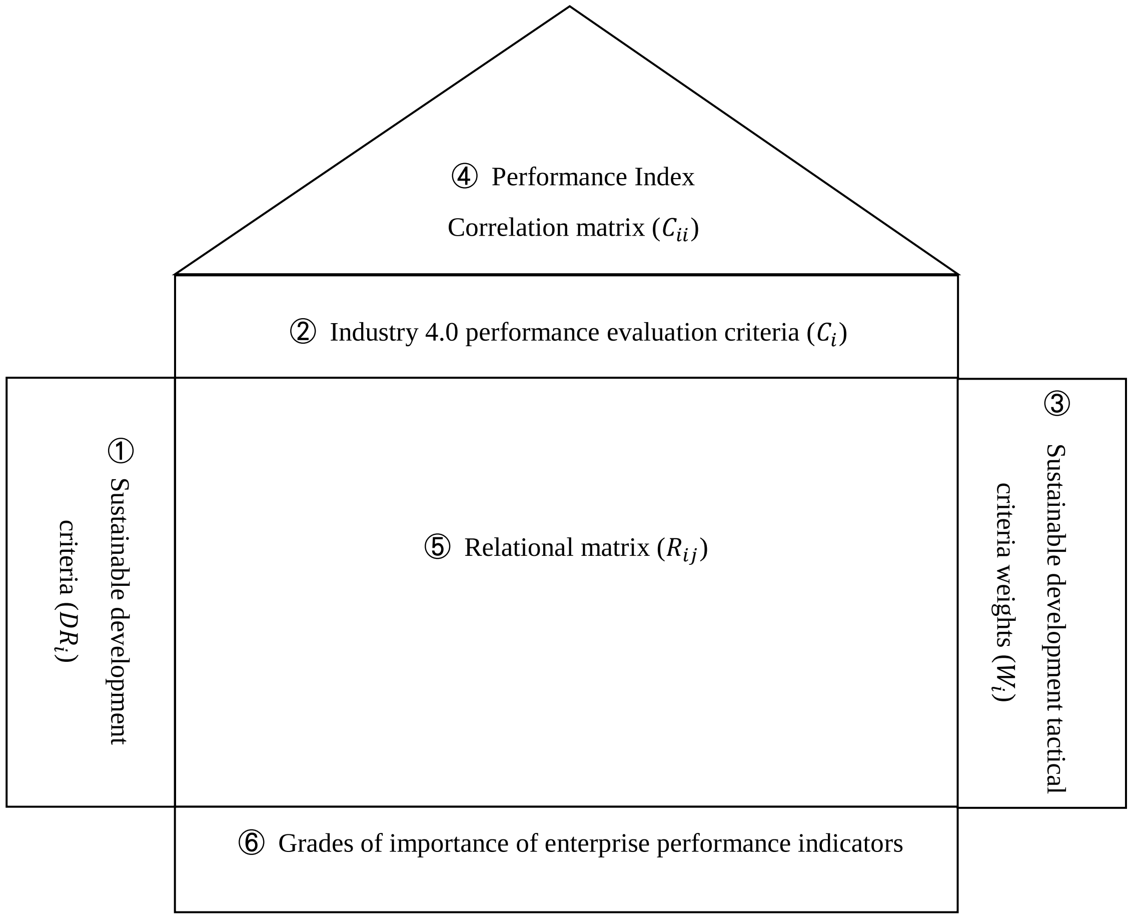


Figure 3

Organizational chart of the house of quality in this study.

Step 1: Use FDM to recover the expert questionnaires to determine ① sustainable development criteria and ② performance indicators.

Step 2: Use revised FEAHP to evaluate ③ the relative weights of sustainable development criteria (W).

Step 3: Use fuzzy theory to evaluate the expert questionnaires to obtain ④ the correlation matrices of performance indicators (C), and ⑤ the relational matrices of enterprise performance indicators and sustainable development criteria (R).

Step 4: Calculate the integrated relational matrix (IR) by multiplying the correlation matrices (C) and the relational matrices (R).

Step 5: Use the TOPSIS method to find the final weighted values of performance indicators ⑥ and sort priority.

3.2 Fuzzy set theory

The main purpose of the fuzzy set theory is to express clearly objects of subjectivity and uncertainty through the membership function. $\widetilde{A}$ is set as the fuzzy set of U, and $\widetilde{\mu}_{\tilde{A}}(x_i)$ is called x in the membership function of $\widetilde{A}$. When the membership degree is 1, it implies that the fuzzy prediction completely complies with the objective; when the membership degree is 0, it means that the fuzzy prediction does not fit this objective (Figure. 4). This study used triangular fuzzy numbers expressed as $\widetilde{\mu}_{\tilde{A}}(x_i) = (a, b, c)$, where the μ of a $\leq$ b $\leq$ c and a $\geq$ 0 is called the positive triangular fuzzy number.

Suppose two triangular fuzzy numbers, $\widetilde{A} = (a_1, b_1, c_1)$ and $\widetilde{B} = (a_2, b_2, c_2)$, and the fuzzy values of $\widetilde{A}$ and $\widetilde{B}$ are greater than 0,then the four arithmetic operations are as follows:

Addition : $\tilde{A}+\tilde{B} = (a_1+a_2,\ b_1+b_2,\ c_1+c_2)$ (1)

Subtraction : $\tilde{A}-\tilde{B} = (a_1 - c_2,\ b_1 - b_2,\ c_1\text{-}a_2)$ (2)

Multiplication : $\tilde{A}\times\tilde{B} = (a_1 \times a_2,\ b_1 \times b_2,\ c_1 \times c_2)$ (3)

Division : $\tilde{A}\div\tilde{B} = (a_1 \div c_2,\ b_1 \div b_2,\ c_1 \div a_2)$ (4)

Defuzzification method: This study adopted the relative distance formula (Chen, 2000) for defuzzification. The equation is:

$$R_i = \frac{d^-}{d^- + d^*} \quad (5)$$

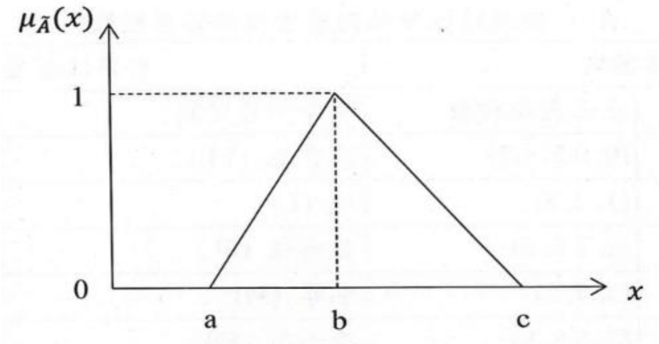


Figure 4
Membership function

where $d^* = (\widetilde{v}, \widetilde{v}^*)$ and $d^- = (\widetilde{v}, \widetilde{v}^-)$. The variable $\widetilde{v}^*$ is the best fuzzy value, and the variable $\widetilde{v}^-$ is the worst fuzzy value. According to the above equation, if *R* = 1, then it represents that $d^* = 0$, meaning that the distance between fuzzy values $\widetilde{v}$ and $\widetilde{v}^*$ is equal to 0. That is, the fuzzy value $\widetilde{v}$ is the best value. If *R* = 0, then $d^- = 0$, meaning that the distance between fuzzy values $\widetilde{v}$ and $\widetilde{v}^-$ is equal to 0. That is, the fuzzy value $\widetilde{v}$ is the worst value. This conversion formula can defuzzify the fuzzy evaluation value $\widetilde{x}_i = (a_i, b_i, c_i)$, using M_1expression as follows:

$$\boldsymbol{M_1}(\tilde{\boldsymbol{x}}_i) = \frac{\boldsymbol{d_i^-}}{\boldsymbol{d_i^-} + \boldsymbol{d_i^*}} \quad , \boldsymbol{i} = \boldsymbol{1}, \boldsymbol{2}, \dots, \boldsymbol{n} \tag{6}$$

where

$$\boldsymbol{d_i^-} = \sqrt{\frac{1}{3}(\boldsymbol{a_i^2} + \boldsymbol{b_i^2} + \boldsymbol{c_i^2})} \tag{7}$$

$$\boldsymbol{d_i^*} = \sqrt{\frac{\boldsymbol{1}}{\boldsymbol{3}}[(\boldsymbol{1} - \boldsymbol{a_i})^2 + (\boldsymbol{1} - \boldsymbol{b_i})^2 + (\boldsymbol{1} - \boldsymbol{c_i})^2]} \tag{8}$$

and, $\boldsymbol{0} \leq \boldsymbol{M_1} \leq \boldsymbol{1}$. The best fuzzy evaluation value is defined as $\tilde{\boldsymbol{v}}^* = (\boldsymbol{1}, \boldsymbol{1}, \boldsymbol{1})$, and the worst fuzzy evaluation value is $\tilde{\boldsymbol{v}}^- = (\boldsymbol{0}, \boldsymbol{0}, \boldsymbol{0})$.

In the evaluation of the correlation matrices of the performance indicators in QFD, this research adopted the semantic fuzzy evaluation, which expresses mild, medium, and strong correlation. Table 5 shows the evaluation values of varying degrees that represent the corresponding semantic descriptions, semantic symbols, and triangular fuzzy values. Through the fuzzy operations and after the defuzzification steps, crisp values were obtained.

Table 5
Semantic fuzzy evaluation of the direct evaluation method

Degree	Semantic Symbols	Triangular Fuzzy Numbers
Mild correlation	○	(0, 0.1, 0.4)
Medium correlation	△	(0.2, 0.5, 0.8)
Strong correlation	◎	(0.6, 0.9, 1.0)

3.3 The Fuzzy Delphi Method

Ishikawa et al. (1993) used the fuzzy theory concept to introduce the Delphi method and established two methods: the cumulative frequency distribution method with max-min values and the fuzzy integral method. The experts' opinions are integrated into a fuzzy number process called the fuzzy Delphi method (FDM). The calculation steps are as follows:

Step 1: For the confirmation of evaluation items, the researcher invites expert scholars and industry managers of related fields to construct an expert group and to give an interval of values to measure the degree of importance of the evaluation objectives. The "minimum value" of the interval represents the "most conservative cognitive value"; the "maximum value" represents the "most optimistic cognitive value."

Step 2: After collecting and compiling the expert questionnaires, the researcher deletes items that fall "two standard deviations" outside the extreme values and then calculates the minimum values, geometric means, and maximum values of the "most conservative cognitive value" and the "most optimistic cognitive value." So, each evaluation item *i* has the triangular fuzzy number of the "most conservative cognitive value," $\boldsymbol{C^i} = (\boldsymbol{C_L^i}, \boldsymbol{C_M^i}, \boldsymbol{C_U^i})$, and the triangular fuzzy number of the "most optimistic cognitive value," $\boldsymbol{O^i} = (\boldsymbol{O_L^i}, \boldsymbol{O_M^i}, \boldsymbol{O_U^i})$, as shown in Figure 5.

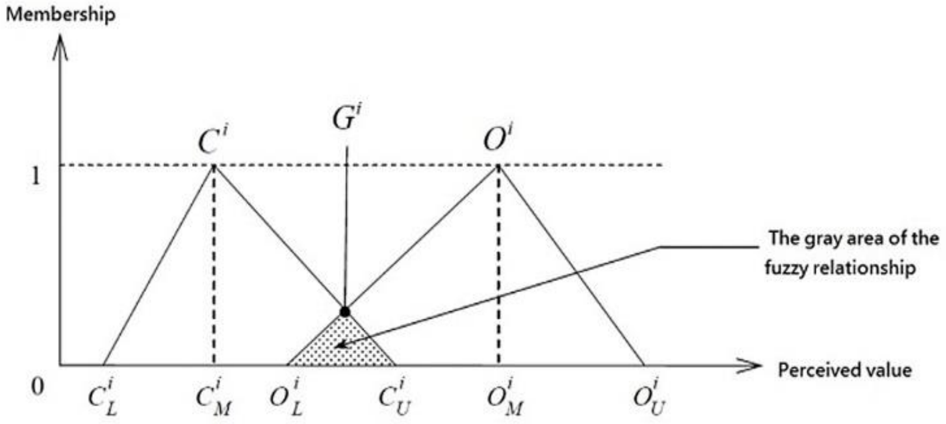


Figure 5
Grey area of fuzzy relations.

Step 3: The researcher calculates the degree of consensus $\boldsymbol{G^i}$, which is the "value of importance degree of consensus." The calculation of $\boldsymbol{G^i}$ has the following three conditions:

1. If two triangular fuzzy numbers do not overlap, then $(\boldsymbol{C_U^i} \leqq \boldsymbol{O_L^i})$. The value of importance degree of consensus," $\boldsymbol{G^i}$, of the evaluation item i is equal to the arithmetic mean of $\boldsymbol{C_M^i}$ and $\boldsymbol{O_M^i}$. This is expressed as

$$\boldsymbol{G^i} = (\boldsymbol{C_M^i} + \boldsymbol{O_M^i})/\boldsymbol{2} \tag{9}$$

2. If two triangular fuzzy numbers overlap, then $(\boldsymbol{C_U^i} > \boldsymbol{O_L^i}$ and $\boldsymbol{Z^i}<\boldsymbol{M^i}$, where $\boldsymbol{Z^i} = \boldsymbol{O_M^i} - \boldsymbol{C_M^i}$, which represents that the grey area of the fuzzy relationships is smaller than the experts' interval $(\boldsymbol{M^i} = \boldsymbol{O_M^i} - \boldsymbol{C_M^i})$ of the evaluation item's "geometric mean of optimistic cognition" and "geometric mean of the conservative cognition." Although the interval values of experts' opinions have no segment of consensus, the experts that gave opinions at the extreme end did not differ too greatly from the opinions of other experts. Then the "value of importance degree of consensus" of the evaluation item *i* is calculated using Equation (10).

$$\boldsymbol{G^i} = [(\boldsymbol{C_U^i} * \boldsymbol{O_M^i}) - (\boldsymbol{O_L^i} * \boldsymbol{C_M^i})]/[(\boldsymbol{C_U^i} - \boldsymbol{C_M^i}) - (\boldsymbol{O_M^i} - \boldsymbol{O_L^i})] \tag{10}$$

3. If two triangular fuzzy numbers overlap, then ($C_U^i > O_L^i$) and $Z^i = O_M^i - C_M^i$, which represents that the interval values of the experts have no consensus segment, and that the interval values of the experts' opinions have no consensus, and represents that the differences in experts' opinions are too great, leading to a divergence of opinions. Thus the non-converging evaluation items can be provided as reference to experts to conduct another round of the questionnaire survey until the evaluation items have all reached convergence and the "value of importance degree of consensus" has been found.

3.4. Fuzzy extended analytical hierarchy process

Chang (1992, 1996) proposed the fuzzy extended analytic hierarchy process (FEAHP). Because of the simplicity of the implementation steps, many studies have adopted this method. However, in many studies, the application of this method obtained a number of criteria weight values of 0, which appeared unreasonable in the real case. Due to this disadvantage, this study proposes the modified method.

Before the introduction of the fuzzy analytical hierarchy process, we adopted the fuzzy Delphi method proposed by Hsu & Yang's (2000) to produce the fuzzy synthetic comparison matrix from the evaluation values of traditional AHP of experts. The method still takes the opinions of experts' maximum value and minimum value as the two endpoints of a triangular fuzzy number, and the geometric mean as the membership degree of the triangular fuzzy number, to compile and convert the values into the triangular fuzzy number $\tilde{T}_i = (L_i, M_i, U_i)$. The conversion pro-cess is as follows:

$$L_i = Min(X_i) \tag{11}$$

$$M_i = \sqrt[n]{\prod_{i=1}^{n} X_i} \tag{12}$$

$$U_i = Max(X_i) \tag{13}$$

where, i = 1, …, n is the number of experts, X_i represents the evaluation values of pairwise comparisons of evaluation variables by the experts, i. L_i is the minimum evaluation value, U_i is the maximum evaluation value, and M_i is the geometric mean of all evaluation values.

Suppose that $X = \{x_1, x_2, x_3, \ldots, x_n\}$ is the object set, and $U = \{u_1, u_2, u_3, \ldots, u_m\}$ is the goal set. According to the extent analysis method of Chang (1992, 1996), each object is respectively brought into each goal for extent analysis. The fuzzy number is used to quantify the "degree." Therefore, each object gets the value of m degree analysis, expressed as follows:

$$M_{gi}^{1}, M_{gi}^{2}, \ldots, M_{gi}^{m}, i = 1, 2, \ldots, \tag{14}$$

where $M_{gi}^{j} (j = 1, 2, \ldots, m)$ are triangular fuzzy numbers (TFNs). The procedure for the calculation is as follows:

Step 1: The fuzzy synthetic extent value of No. *i* object is defined as follows:

$$S_i = \sum_{j=1}^{m} M_{gi}^{j} \odot \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right]^{-1} \tag{15}$$

where $\sum_{j=1}^{m} M_{gi}^{j}$ is the fuzzy addition operation of m degree analysis value.

$$\sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j \right) \tag{16}$$

And $\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right]$ is the fuzzy addition operation of $M_{gi}^{j} (j = 1, 2, \text{ fum})$ value.

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right] = \left(\sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i \right) \tag{17}$$

Then the vector inverse matrix of Equation (15) is calculated as follows:

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i} \right) \tag{18}$$

Step 2: The possibility degree of $M_2 = (l_2, m_2, u_2) \geq M_1 = (l_1, m_1, u_1)$ is defined as follows:

$$V_{(M_2 \geq M_1)} = sup_{y \geq x} \left[min\left(\mu_{M1}{}^{(x)}, \mu_{M2}{}^{(y)} \right) \right] \tag{19}$$

Because M_1 and M_2 are convex fuzzy numbers, therefore

$$V_{(M_2 \geq M_1)} = hgt_{(M_1 \cap M_2) = \mu_{M2}(d)} = \begin{bmatrix} 1, & \text{if } m_2 > m_1 \\ 0, & \text{if } l_1 \geq u_2 \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & \text{otherwise,} \end{bmatrix} \tag{20}$$

where, d value is a point D vertically extended to the value of the X axis, and point D is the highest point of the intersection of M_1 and M_2 (Figure. 6).

In order to compare M_1 and M_2, the values of $V_{(M_1 \geq M_2)}$ and $V_{(M_2 \geq M_1)}$ must be calculated in conjunction.

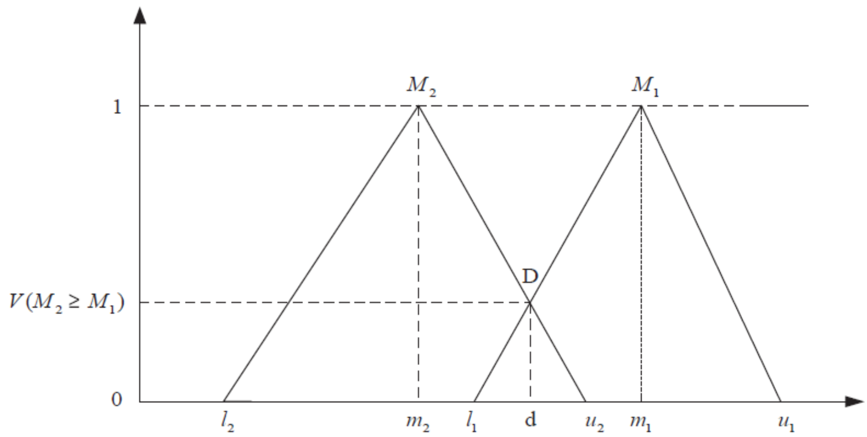


Figure 6

The intersection of the triangular fuzzy numbers $\boldsymbol{M_1}$ and $\boldsymbol{M_2}$

Step 3: The convex fuzzy number is greater than the possibility of other k convex fuzzy numbers, $\boldsymbol{M_i(i=1,2,\ldots,k)}$, defined as follows:

$$\boldsymbol{V}_{(\boldsymbol{M \geq M_1, M_2, \ldots, M_k})} = \boldsymbol{V}_{[(\boldsymbol{M \geq M_1}),(\boldsymbol{M \geq M_2}),\ldots,(\boldsymbol{M \geq M_k})]} = \boldsymbol{minV}_{(\boldsymbol{M \geq M_i}),} \quad \boldsymbol{i=1\ldots,k}$$

If

$$\boldsymbol{d'(A_i) = minV}_{(\boldsymbol{S_i \geq S_k})} \quad (21)$$

where, k=1,2,⋯,n；k≠i. The weight vector obtained is:

$$\boldsymbol{W' = \left(d'(A_1), d'(A_2), \ldots, d'(A_n)\right)^T} \quad (22)$$

where, $\mathbf{A_1}\boldsymbol{(i=1,2,\ldots n)}$ is n number of elements.

Step 4: The weight vector after normalization is

$$\mathbf{W} = \boldsymbol{\left(d(A_1), d(A_2), \ldots, d(A_n)\right)^T} \quad (23)$$

where, W is a defuzzified weighted importance value.

3.5 The technique for order of preference by similarity to ideal solution

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), developed by Hwang & Yoon (1981). The TOPSIS method must first establish the positive ideal solution (PIS) and negative ideal solution (NIS). PIS is composed of the maximum value of the benefit criteria or the minimum value of cost criteria. Conversely, NIS is composed of the minimum value of the benefit criteria or maximum value of cost criteria. The alternative closest to the positive ideal solution and farthest from the negative ideal solution is selected as the best alternative. The steps of the TOPSIS analysis are detailed as follows:

Step 1: Establish the normalized evaluation matrix (R). The equation is:

$$r_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{s} X_{ij}^2}} \tag{24}$$

where *i* is the alternative, *j* is the evaluation criteria, and X_{ij} represents alternate *i* in the evaluation value under *j* criterion.

Step 2: Establish the normalized weight vector V, which multiplies by the normalized evaluation matrix (R) by W = ($W_1, W_2, \ldots, W_j, \ldots, W_n$). That is,

$$V = \begin{bmatrix} V_{11} & V_{12} \cdots V_{1n} \\ V_{21} & V_{22} \cdots V_{2n} \\ \vdots & \vdots \ \vdots \ \vdots \\ V_{m1} & V_{m2} \cdots V_{mn} \end{bmatrix} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \cdots & w_n r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ w_1 r_{m1} & w_2 r_{m1} & \cdots & w_n r_{mn} \end{bmatrix} \tag{25}$$

where $V = [V_{ij}]_{m \times n}, i = 1, 2, \ldots, m\ ; j = 1, 2, \ldots, n$

Step 3: Decide the PIS V^+ and NIS V^- : Under the m evaluation alternatives and n evaluation criteria, the equations are:

$$\text{PIS}: V^+ = \{v_1^+, v_2^+, \cdots, v_n^+\} \tag{26}$$

$$\text{NIS}: V^- = \{v_1^-, v_2^-, \cdots, v_n^-\} \tag{27}$$

Step 4: Calculate the distance of the evaluation alternatives from the positive ideal solution and negative ideal solution. According to the Euclidean distance formula, calculate the separation measure from the alternatives to PIS and NIS. Respectively calculate S_i^+ and S_i^- as follows:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2} \quad , i = 1, 2, \ldots, m\ ; j = 1, 2, \ldots, n \tag{28}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \quad , i = 1, 2, \ldots, m\ ; j = 1, 2, \ldots, n \tag{29}$$

Step 5: Calculate the relative performance indicator values.

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{30}$$

Step 6: Rank according to the value of C_i. When $0 \leq C_i \leq 1$, the closer C_i gets to 1, the better the evaluation alternative are.

4. Application examples

This empirical study focuses on practical applications in the machine tool industry. To achieve this, experts from machine tool-related industries were invited to conduct a questionnaire survey. The interviewees work in industrial categories related to metal processing machinery manufacturing and repairing industries, as well as special production machinery manufacturing and repairing industries. The interviewees had work experience ranging from 8 to 20 years and held professional titles, at least at the specialist or section chief level. Respondents possess sufficient experience and knowledge to complete the questionnaire. This study divided the questionnaire into two stages. The first stage involved the FDM expert questionnaire designed to screen out representative Industry 4.0 and SD indicator factors. A total of 10 questionnaires were distributed, and all 10 were recovered, resulting in a recovery rate of 100%. In the second stage, three different types of questionnaires were designed, (1) to evaluate the weighted importance of SD; (2) to assess the correlation between Industry 4.0 performance indicators; and (3) to explore the comprehensive relationship between SD and Industry 4.0 indicators. A total of 10 questionnaires were distributed and 10 were recovered, with a recovery rate of 100%. The steps of this study are as follows.

Step 1: Selection of Sustainable Development Criteria and Industry 4.0 Performance Indicators.

The research reviewed and compiled the relevant literature, summarizing the key indicators of SD and Industry 4.0. Through the expert questionnaire survey, according to Equations (9) and (10), SD criteria and Industry 4.0 performance indicators were selected. Encode the SD criteria as (DR) and set the threshold value $\boldsymbol{G^i}$>5.85. After the selection of SD criteria, of the original 28 items, 15 items were left; Industry 4.0 uses ($\boldsymbol{C^i}$) as the code name and sets the threshold $\boldsymbol{G^i}$>6.20, after the selection of performance indicators, of the original 23 items, 17 items were left. The results shown in Table 6 are the criteria items ①and ②, respectively, as seen in Figure. 3, the House of quality structure.

Step 2: Sustainable Development Criteria Weight Evaluation.

This study used the modified fuzzy extended analytic hierarchy process (FEAHP) to conduct the weight evaluation of sustainable development criteria. First, after receiving the questionnaires, this study conducted integration and transformation into a triangular fuzzy number (a, b, c), in which a is the minimum evaluation value of criterion C; c is the maximum evaluation value of criterion C; b is the geometric mean in the evaluation values of criterion C. For example, the weight evaluation of “environment compared with economy” has 10 experts. The evaluation values are (4, 7, 3, 2, 7) respectively. Applying Equation. (11) -(13), the triangular fuzzy number of the importance of “environment on economy” is (2, 4.11, 7). Therefore, the fuzzy evaluation of the pair-wise relative importance of the economy (C_1), society (C_2), and environment (C_3) is as shown in Table 7.

The calculation processes of the weight vector (W_g) of the SD dimension are as follows. The fuzzy integration degrees of three different criteria (C1~C3) are respectively represented by F_1, F_2, and F_3 and brought into Equation (15).

F_1 = (6.00, 10.05, 15.00)×(0.04, 0.07, 0.11) = (0.24, 0.70, 1.65).

F_2 = (1.46, 2.55, 7.34)×(0.04, 0.07, 0.11) = (0.06, 0.18, 0.81).

F_3 = (1.31, 2.05, 4.40)×(0.04, 0.07, 0.11) = (0.05, 0.14, 0.48).

The results were then brought into Equation (20) to analyze the possible degree of F_i with respect to F_j ($i \neq j$).

$V(F_1 \geq F_2) = 1$, $V(F_1 \geq F_3) = 1$, $V(F_2 \geq F_3) = 1$

$V(F_2 \geq F_1)$ = (0.24-0.81)/〔(0.18-0.81)-(0.70-0.24)〕=0.523

$V(F_3 \geq F_1)$ = (0.24-0.48)/〔(0.14-0.48)-(0.70-0.24)〕=0.300

$V(F_3 \geq F_2)$ = (0.06-0.48)/〔(0.14-0.48)-(0.18-0.06)〕=0.913

After the possible degree was explored, Equation (21) was used to obtain the weight vectors.

Table 6

FDM analysis results of this study

Factor code	Indicator factors	G^i value	Factor code	Indicator factors	G^i value
DR_1	Reduce manufacturing costs.	5.87	C_1	Cyber-Physical System	7.02
DR_2	Reduce procurement costs.	6.50	C_2	Lean Production	7.36
DR_3	Enhance product quality.	6.93	C_3	Smart Manufacturing	7.60
DR_4	Enhance proportion of on-time delivery.	7.08	C_4	Manufacturing Execution System	6.87
DR_5	Reduce transport time.	5.92	C_5	Enterprise Resource Planning	6.78
DR_6	Improve manufacturing technology.	5.87	C_6	Industrial Internet of Things	6.21
DR_7	Reduce the incidence of health and safety problems in the enterprise.	7.09	C_7	Big Data	6.53
DR_8	Reduce the incidence of discrimination cases.	6.71	C_8	Digital Product-Service Systems	6.67
DR_9	Senior management's commitment to SD	6.40	C_9	Smart Product /Intelligent Product	6.51
DR_{10}	Enhance the safety and health of customers in using products.	6.40	C_{10}	Smart Electric Grid/Intelligent Grid	7.13
DR_{11}	Reduce the amount of harmful substances produced.	6.06	C_{11}	Digital automation with sensors	7.83
DR_{12}	Reduce greenhouse gas emissions	5.87	C_{12}	Wireless Sensor Network	6.86
DR_{13}	Reduce water usage.	6.50	C_{13}	Automation	7.83
DR_{14}	Green Supply Chain	5.92	C_{14}	Supervisory Control and Data Acquisition	7.63
DR_{15}	Obtain the relevant environmental certifications.	6.82	C_{15}	Flexible Manufacturing Lines	6.84
			C_{16}	Simulations/Analysis of Virtual Models	6.69
			C_{17}	Computer-Aided Design and Manufacturing	6.67

Table 7

Fuzzy evaluation of importance under sustainable development.

Dimension	C_1	C_2	C_3	Wg
C_1	(1.00,1.00,1.00)	(0.15,0.25,0.50)	(0.18,0.79,3.00)	0.2934
C_2	(2.00,4.11,7.00)	(1.00,1.00,1.00)	(2.95,4.95,7.90)	0.4133
C_3	(0.33,1.25,5.90)	(0.13,0.30,0.34)	(1.00,1.00,1.00)	0.2934

$\min(\boldsymbol{F_1})$ = $\min\boldsymbol{V}(\boldsymbol{F_1} \geq \boldsymbol{F_2}, \boldsymbol{F_3})$ = min(1,1) = 1.00

$\min(\boldsymbol{F_2})$ = $\min\boldsymbol{V}(\boldsymbol{F_2} \geq \boldsymbol{F_1}, \boldsymbol{F_3})$ = min(0.523,1) = 0.523

$\min(\boldsymbol{F_3})$ = $\min\boldsymbol{V}(\boldsymbol{F_3} \geq \boldsymbol{F_1}, \boldsymbol{F_2})$ = min(0.300,0.9432) = 0.300

Therefore, after the normalization of the weight vector $\boldsymbol{W_g} = (\boldsymbol{1}, \boldsymbol{0.523}, \boldsymbol{0.300})^{\boldsymbol{T}}$, we got $\boldsymbol{W_g} = (\boldsymbol{1}, \boldsymbol{0.523}, \boldsymbol{0.300})^{\boldsymbol{T}}$. Finally, the weight values of the three dimensions are shown in Table 8. Following the same procedures, the importance weight of SD criteria can be determined also as shown in Table 8.

Table 8
Degree of importance of criteria under sustainable development and the three dimensions of sustainable development.

Sustainability Development Dimension	Dimension Weight	Sustainability Development Index	Local Weight	Integrated Weight
Economy dimension (C_1)	0.2934	DR_1	0.1931	0.0567
		DR_2	0.2887	0.0847
		DR_3	0.2074	0.0609
		DR_4	0.2727	0.0800
		DR_5	0.2708	0.0795
		DR_6	0.1884	0.0553
Society dimension (C_2)	0.4133	DR_7	0.1724	0.0713
		DR_8	0.3038	0.1256
		DR_9	0.1975	0.0816
		DR_{10}	0.1664	0.0688
Environment dimension (C_3)	0.2934	DR_{11}	0.0839	0.0246
		DR_{12}	0.1368	0.0400
		DR_{13}	0.0513	0.0151
		DR_{14}	0.2963	0.0869
		DR_{15}	0.2355	0.0690

Step 3: Relational Evaluation of Sustainable Development Criteria and Performance Indicators.

In order to evaluate the relations between SD criteria and performance indicators, and the correlation among performance indicators of the semantic assessment, in terms of mild, medium, and high relation were adopted, and converted into triangular fuzzy numbers. After the arithmetic mean was obtained, Equations (5) -(8) were used for defuzzification. Take the relation of C_1 (Cyber-Physical System) and DR_3 (Enhance product quality) as an example, after 10 questionnaires were integrated, the triangular fuzzy number was (0.08, 0.26, 0.56). Equation (7) calculated $\boldsymbol{d_1^-}$=0.36, and Equation (8) calculated $\boldsymbol{d_i^*}$=0.73. Equation (5) calculated the relation of C_1 (Cyber-Physical System) and DR_3 (Enhance product quality) to be $\boldsymbol{R_1} =$

$\boldsymbol{d^-/(d^- + d^*) = 0.36/(0.36 + 0.73) = 0.33}$. This step can obtain the relational matrices (Table 9) and correlation matrices (Table 10) and complete ③ and ④ of the house of quality.

Step 4: TOPSIS Method to Obtain Key Performance Indicators

Step 4.1: obtain the integrated relational matrices The integrated relational matrices with all associative factors considered must be obtained by multiplying the relational matrices and the correlation matrices. The matrix is the calculation basis of TOPSIS. Table 11 shows the multiplication results.

Step 4.2: calculate the normalized integrated relational matrices After obtaining the integrated relational matrices, Equation (24) and (25) are used to calculate the normalized integrated relational matrices and the importance weight of sustainable development criteria as Table 12.

Step 4.3: prioritize the performance indicators Each associated performance indicator was compared to the positive ideal solution and negative ideal solution in Table 13. Equations (26) and (27) were used to find the solutions.

The distance between each performance indicator and the PIS and NIS were calculated. The Euclidean distance equation was used to calculate the degree of separation between performance indicators being evaluated. After Equations (28) and (29) were used to find the solutions, Equation (30) was used to calculate C_i. The performance indicators were presented in order of relative merits. The results are shown in Table 14, and all results were compiled in the house of quality in Figure. 7.

Table 9
Relational matrices of sustainable development criteria and Industry 4.0 performance indicators.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}
DR_1	0.00	0.22	0.22	0.22	0.22	0.43	0.31	0.69	0.22	0.68	0.78	0.67	0.41	0.50	0.61	0.69	0.78
DR_2	0.64	0.67	0.50	0.50	0.40	0.71	0.71	0.78	0.50	0.78	0.50	0.68	0.50	0.67	0.36	0.00	0.50
DR_3	0.33	0.31	0.22	0.29	0.22	0.22	0.22	0.50	0.36	0.64	0.40	0.40	0.50	0.78	0.22	0.64	0.22
DR_4	0.71	0.59	0.78	0.78	0.78	0.57	0.31	0.22	0.22	0.40	0.78	0.50	0.78	0.22	0.22	0.50	0.22
DR_5	0.69	0.43	0.67	0.67	0.65	0.50	0.29	0.50	0.22	0.50	0.78	0.64	0.22	0.41	0.00	0.50	0.00
DR_6	0.78	0.50	0.73	0.62	0.65	0.43	0.36	0.50	0.50	0.50	0.78	0.43	0.50	0.50	0.50	0.00	0.00
DR_7	0.36	0.22	0.22	0.22	0.22	0.22	0.41	0.22	0.78	0.00	0.00	0.50	0.22	0.00	0.00	0.41	0.41
DR_8	0.36	0.22	0.22	0.22	0.22	0.22	0.41	0.22	0.22	0.00	0.00	0.22	0.78	0.56	0.00	0.36	0.36
DR_9	0.36	0.31	0.22	0.67	0.22	0.22	0.41	0.22	0.22	0.00	0.00	0.22	0.68	0.56	0.00	0.50	0.50
DR_{10}	0.22	0.22	0.22	0.22	0.22	0.22	0.50	0.22	0.22	0.00	0.00	0.00	0.22	0.50	0.50	0.36	0.36
DR_{11}	0.43	0.64	0.22	0.22	0.22	0.22	0.36	0.00	0.00	0.00	0.00	0.00	0.71	0.50	0.00	0.22	0.22
DR_{12}	0.31	0.31	0.27	0.41	0.22	0.31	0.31	0.22	0.38	0.50	0.22	0.41	0.71	0.60	0.22	0.78	0.00
DR_{13}	0.22	0.64	0.00	0.29	0.00	0.00	0.50	0.00	0.00	0.00	0.36	0.00	0.68	0.78	0.22	0.68	0.78
DR_{14}	0.00	0.00	0.22	0.00	0.00	0.22	0.50	0.60	0.69	0.78	0.50	0.69	0.50	0.78	0.22	0.22	0.00
DR_{15}	0.22	0.78	0.22	0.67	0.00	0.00	0.00	0.41	0.41	0.41	0.50	0.00	0.68	0.78	0.50	0.65	0.71

The bold values signify no relation.

Table 10
Correlation matrices between performance indicators

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}
C_1	**1.00**	0.44	0.39	0.45	0.43	0.33	0.78	0.73	0.50	0.61	0.67	0.78	0.61	0.45	0.78	0.78	0.57
C_2	0.78	**1.00**	0.33	0.33	0.36	0.36	0.73	0.61	0.33	0.50	0.73	0.73	0.39	0.39	0.78	0.61	0.29
C_3	0.73	0.50	**1.00**	0.44	0.41	0.22	0.73	0.73	0.39	0.50	0.73	0.67	0.50	0.36	0.78	0.73	0.29
C_4	0.78	0.36	0.29	**1.00**	0.43	0.44	0.78	0.73	0.44	0.56	0.78	0.62	0.62	0.44	0.68	0.73	0.65
C_5	0.67	0.39	0.33	0.61	**1.00**	0.33	0.62	0.67	0.39	0.55	0.73	0.73	0.38	0.44	0.73	0.73	0.40
C_6	0.78	0.39	0.36	0.50	0.33	**1.00**	0.68	0.78	0.33	0.56	0.73	0.68	0.45	0.27	0.68	0.78	0.29
C_7	0.78	0.27	0.22	0.43	0.39	0.33	**1.00**	0.29	0.55	0.56	0.36	0.22	0.55	0.22	0.22	0.33	0.33
C_8	0.45	0.27	0.22	0.27	0.33	0.29	0.33	**1.00**	0.44	0.61	0.55	0.56	0.44	0.67	0.56	0.50	0.33
C_9	0.61	0.78	0.61	0.44	0.45	0.78	0.56	0.50	**1.00**	0.44	0.39	0.27	0.44	0.61	0.27	0.50	0.32
C_{10}	0.50	0.44	0.78	0.44	0.50	0.44	0.39	0.36	0.55	**1.00**	0.33	0.33	0.61	0.78	0.29	0.39	0.44
C_{11}	0.33	0.78	0.78	0.50	0.55	0.78	0.44	0.22	0.73	0.44	**1.00**	0.27	0.50	0.78	0.22	0.33	0.32
C_{12}	0.45	0.78	0.67	0.32	0.61	0.78	0.44	0.36	0.61	0.61	0.44	**1.00**	0.61	0.61	0.33	0.36	0.33
C_{13}	0.43	0.55	0.45	0.50	0.61	0.61	0.43	0.41	0.67	0.50	0.33	0.39	**1.00**	0.61	0.55	0.39	0.22
C_{14}	0.61	0.61	0.44	0.27	0.27	0.50	0.62	0.50	0.44	0.44	0.38	0.45	0.27	**1.00**	0.55	0.33	0.73
C_{15}	0.57	0.73	0.44	0.73	0.44	0.61	0.44	0.39	0.44	0.55	0.39	0.33	0.44	0.67	**1.00**	0.36	0.27
C_{16}	0.45	0.50	0.44	0.39	0.27	0.32	0.61	0.44	0.39	0.44	0.50	0.43	0.73	0.50	0.20	**1.00**	0.73
C_{17}	0.57	0.44	0.33	0.73	0.22	0.32	0.65	0.29	0.27	0.32	0.40	0.29	0.73	0.33	0.33	0.29	**1.00**

The bold values signify no relation.

Table 11
Integrated relational matrices

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}
DR_1	4.14	3.44	3.34	4.12	3.65	3.24	3.28	4.09	3.89	4.67	4.34	4.51	3.46	4.34	3.99	3.98	3.55
DR_2	4.95	4.78	4.83	4.83	4.32	5.35	5.35	4.46	4.54	4.97	4.53	4.92	4.53	4.78	4.28	1.94	4.53
DR_3	3.75	3.20	3.15	3.68	3.26	3.01	3.05	3.39	3.43	3.84	3.47	3.77	2.98	3.77	3.25	3.40	3.00
DR_4	5.35	4.86	4.80	5.37	5.03	4.68	4.72	3.75	4.41	4.34	4.00	4.36	4.80	3.89	3.98	4.12	3.68
DR_5	4.80	4.38	4.30	4.78	4.52	4.16	4.11	3.79	4.13	4.20	3.94	4.24	3.46	4.20	3.70	3.77	3.27
DR_6	5.26	4.71	4.63	5.05	4.77	4.46	4.67	4.04	4.61	4.56	4.31	4.57	3.92	4.31	4.27	3.67	3.25
DR_7	3.14	2.62	2.69	3.08	2.79	2.62	2.71	2.25	2.92	2.44	2.18	2.60	2.07	1.94	2.29	2.64	2.40
DR_8	2.63	2.21	2.28	2.58	2.31	2.20	2.30	1.68	2.15	1.93	1.69	1.94	4.31	2.42	1.76	2.17	2.05
DR_9	2.84	2.39	2.44	4.30	2.50	2.36	2.46	1.82	2.30	2.11	1.81	2.09	4.92	2.66	1.89	2.44	2.32
DR_{10}	2.60	2.13	2.22	2.53	2.26	2.13	4.16	1.67	2.15	2.01	1.73	1.95	1.59	2.34	1.99	2.13	1.97
DR_{11}	2.24	4.95	1.97	2.18	1.95	1.94	2.06	1.10	1.60	1.39	1.18	1.35	5.35	1.89	1.32	1.63	1.60
DR_{12}	3.59	3.15	3.16	3.57	3.23	3.04	3.04	2.87	3.24	3.33	2.98	3.35	5.35	3.43	2.99	3.17	2.69
DR_{13}	1.86	4.95	1.40	3.68	1.44	1.38	4.16	1.55	1.51	1.92	1.68	1.85	4.92	2.36	1.55	2.22	2.23
DR_{14}	2.80	2.28	2.30	2.63	2.35	2.16	4.16	3.36	3.09	3.64	3.44	3.69	2.82	3.10	3.01	2.67	2.18
DR_{15}	2.90	5.26	2.25	4.30	2.34	2.15	2.28	2.77	2.66	3.18	2.78	3.00	4.92	3.24	2.66	2.98	2.79

Table 12
Normalized integrated relational matrices after being weighted

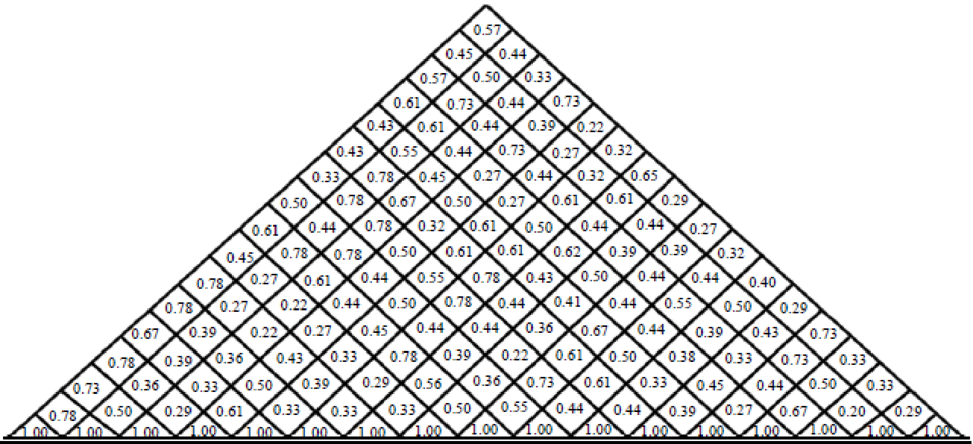
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}
DR_1	0.02	0.01	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02	0.02	0.02
DR_2	0.03	0.03	0.03	0.03	0.03	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.03	0.01	0.03
DR_3	0.02	0.01	0.02	0.01	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02	0.02	0.02
DR_4	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.03	0.03	0.03
DR_5	0.03	0.02	0.03	0.03	0.03	0.03	0.02	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.03	0.03	0.02
DR_6	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02	0.02	0.02
DR_7	0.02	0.01	0.02	0.01	0.02	0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02
DR_8	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.02	0.02	0.02
DR_9	0.02	0.01	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.03	0.02	0.01	0.02	0.02
DR_{10}	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
DR_{11}	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
DR_{12}	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
DR_{13}	0.01	0.03	0.01	0.02	0.01	0.01	0.03	0.01	0.01	0.01	0.01	0.01	0.03	0.02	0.01	0.02	0.02
DR_{14}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DR_{15}	0.01	0.02	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

Table 13
Positive ideal solutions in the association of performance indicators

	DR_1	DR_2	DR_3	DR_4	DR_5	DR_6	DR_7	DR_8	DR_9	DR_{10}	DR_{11}	DR_{12}	DR_{13}	DR_{14}	DR_{15}
V^+	0.02	0.01	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02
V^-	0.03	0.03	0.03	0.03	0.03	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.03

Table 14
Ranking of performance indicators

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}
S_i^+	0.028	0.028	0.029	0.023	0.030	0.030	0.026	0.032	0.030	0.031	0.032	0.031	0.027	0.025	0.030	0.031	0.023
S_i^-	0.024	0.029	0.026	0.026	0.024	0.028	0.029	0.024	0.024	0.024	0.024	0.024	0.031	0.025	0.023	0.022	0.027
C_i	0.463	0.507	0.469	0.538	0.448	0.484	0.530	0.433	0.444	0.437	0.426	0.434	0.536	0.495	0.434	0.415	0.540
Rank	9	5	8	2	10	7	4	15	11	12	16	14	3	6	13	17	1



	Weight	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}
DR_1	0.0567	0.00	0.22	0.22	0.22	0.22	0.43	0.31	0.69	0.22	0.68	0.78	0.67	0.41	0.50	0.61	0.69	0.78
DR_2	0.0847	0.64	0.67	0.50	0.50	0.40	0.71	0.71	0.78	0.50	0.78	0.50	0.68	0.50	0.67	0.36	0.00	0.50
DR_3	0.0609	0.33	0.31	0.22	0.29	0.22	0.22	0.22	0.50	0.36	0.64	0.40	0.40	0.50	0.78	0.22	0.64	0.22
DR_4	0.0800	0.71	0.59	0.78	0.78	0.78	0.57	0.31	0.22	0.22	0.40	0.78	0.50	0.78	0.22	0.22	0.50	0.22
DR_5	0.0795	0.69	0.43	0.67	0.67	0.65	0.50	0.29	0.50	0.22	0.50	0.78	0.64	0.22	0.41	0.00	0.50	0.00
DR_6	0.0553	0.78	0.50	0.73	0.62	0.65	0.43	0.36	0.50	0.50	0.50	0.78	0.43	0.50	0.50	0.50	0.00	0.00
DR_7	0.0713	0.36	0.22	0.22	0.22	0.22	0.22	0.41	0.22	0.78	0.00	0.00	0.50	0.22	0.00	0.00	0.41	0.41
DR_8	0.1256	0.36	0.22	0.22	0.22	0.22	0.22	0.41	0.22	0.22	0.00	0.00	0.22	0.78	0.56	0.00	0.36	0.36
DR_9	0.0816	0.36	0.31	0.22	0.67	0.22	0.22	0.41	0.22	0.22	0.00	0.00	0.22	0.68	0.56	0.00	0.50	0.50
DR_{10}	0.0688	0.22	0.22	0.22	0.22	0.22	0.22	0.50	0.22	0.22	0.00	0.00	0.00	0.22	0.50	0.50	0.36	0.36
DR_{11}	0.0246	0.43	0.64	0.22	0.22	0.22	0.22	0.36	0.00	0.00	0.00	0.00	0.00	0.71	0.50	0.00	0.22	0.22
DR_{12}	0.0400	0.31	0.31	0.27	0.41	0.22	0.31	0.31	0.22	0.38	0.50	0.22	0.41	0.71	0.60	0.22	0.78	0.00
DR_{13}	0.0151	0.22	0.64	0.00	0.29	0.00	0.00	0.50	0.00	0.00	0.00	0.36	0.00	0.68	0.78	0.22	0.68	0.78
DR_{14}	0.0869	0.00	0.00	0.22	0.00	0.00	0.22	0.50	0.60	0.69	0.78	0.50	0.69	0.50	0.78	0.22	0.22	0.00
DR_{15}	0.0690	0.22	0.78	0.22	0.67	0.00	0.00	0.00	0.41	0.41	0.41	0.50	0.00	0.68	0.78	0.50	0.65	0.71
C_i		0.463	0.507	0.469	0.538	0.448	0.484	0.53	0.433	0.444	0.437	0.426	0.434	0.536	0.495	0.434	0.415	0.54
RANK		9	5	8	2	10	7	4	15	11	12	16	14	3	6	13	17	1

Figure 7
Organizational chart of the house of quality

5. Discussion of the results

The study shows two results as follows. Firstly, it indicates the results of the important evaluation of SD criteria through the FEHAP. Among the SD factors introduced in the machine tool industry, social development (C_2) is the most important dimension, and "Reduce the incidence of discrimination cases" (DR_8) is the most important criterion in (C_2). The dimensions of economic development (C_1) and environmental development (C_3) are equally matched and ranked as the second most important, while "Reduce procurement costs" (DR_2) is listed as the most important criterion in (C_1). The most important of (C_3) is the "Green Supply Chain" (DR_{14}). Further looking at the overall importance weight, the top five factors are “Reducing the incidence of discrimination cases” (DR_8), “Green Supply Chain” (DR_{14}), “Reducing procurement costs” (DR_2), and “Senior management’s commitment to SD” (DR_9) and “Enhance proportion of on-time delivery” (DR_4). These are the five crucial indicator factors for the development of SD in Taiwan's machine tool industry.

Secondly, based on the C_i value, the performance indicators of key Industry 4.0 technologies are obtained.

Research results show that the top five key performance indicators that promote Industry 4.0 are; "Computer-Aided Design and Manufacturing" (DR_{15}) is the first indicator. Next is "Manufacturing Execution System" (DR_4), then "Automation" (DR_{13}), then "Big Data" (DR_7), and finally "Lean Production" (DR_2).

6. Conclusions, limitations and future scope of research

2013 is the first year for the enterprises to shift from precision to intelligence. Industry 4.0 is a topic pursued by the global industries. Industrial transformation is imminent. China's machine tool industry has also embraced this trend, proposing a transformation plan that includes intelligence, automation, and cloudization. The aim is to reduce dependence on manpower, comprehensively upgrade manufacturing equipment, and subsequently introduce integrated solutions. During the process of transformation and upgrading, we encounter challenges such as the EU's Carbon Border Adjustment Mechanism (CBAM) and the impending implementation of Taiwan's carbon fee. The net-zero trend is undoubtedly a shock bomb to enterprises. Due to the threat of climate extremes, net-zero carbon emissions have become a global hot topic. Currently, the world has set 2030 as the medium-term carbon emission reduction target. Achieving net-zero carbon emissions will be the top priority for governments and enterprises worldwide in the next 10 years.

Most of Taiwan's machine tool industry belongs to SMEs, and the scale of its suppliers is even more so that. The Taiwan government has announced that, starting from 2025, listed companies with a paid-in capital of less than 2 billion NTD will be required to compile sustainability reports. This is undoubtedly a shock bomb because the scale and paid-in capital of Taiwan's machine tool industry is within this range. Therefore, it is crucial to determine how to introduce effective measures for the machine tool industry. Considering the limited resources of SMEs, choosing appropriate technical indicators to develop sustainable measures is important. In the strategic decision-making process, it is recommended that machine tool industry managers combine different technical indicators with sustainability measures to find opportunities for sustainability improvements. However, in real situations, it is difficult for SMEs to implement all performance measures simultaneously. Therefore, prioritizing performance indicators will facilitate the systematic implementation of these performance indicators to effectively develop sustainability. Implementing Industry 4.0 technical performance indicators will make the machine tool industry more capable of becoming a sustainable enterprise.

This study combines TBL's SD factors with Industry 4.0 technical performance indicators, aiming to propose a comprehensive framework to reveal feasible ways in which key performance indicators can be used to improve the SD of Taiwan's machine tool industry. This is the first attempt to integrate sustainability factors with Industry 4.0 technology performance indicators and identify key performance indicators from them.

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1. The YMC Management Review is hosted by the YMC Management Association TAIWAN R.O.C.. Articles about management, practical discussions and management cases are all welcome for submission. Three areas are especially encouraged for the paper:
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4. Once you submit your paper it will be blind reviewed by two referees. According to the international conventions, all papers published are not to be paid when your paper is accepted.
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