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Research on the Relationship Between Lean Management and Digital Transformation Strategy and Sustainable Development: A Case Study of the Automotive Industry in Taiwan

Po-Yen Lai [1,*] and An-Yuan Chang [2]

[1] Department of Industrial Engineering and Management, Hsiuping University of Science and Technology, Taichung City 41280, Taiwan
[2] Department of Industrial Management, National Formosa University, Yunlin 632301, Taiwan; ayc@nfu.edu.tw
* Correspondence: poyen@hust.edu.tw; Tel.: +886-4-24961100 (ext. 6410)

Abstract

Sustainable Development (SD) has increasingly become a core strategic direction. This study centers on the automotive industry, serving as the primary focus for both research and empirical analysis. If Taiwan's automotive industry can successfully achieve transformation, it will generate a more advanced multiplier effect on the overall development of Taiwan's industries. The study confirms that Lean Management (LM) and SD can effectively produce synergistic effects. Digital Transformation (DT) is increasingly recognized as a key driver of future business development. Exploring the interrelationships among SD, LM, and DT presents a strategic and practical research direction. Findings from this study suggest that integrating LM and DT can generate synergies that enhance resource efficiency, minimize waste, and improve both environmental and social performance. The primary objective of this study is to develop a structured framework connecting SD, LM, and DT by utilizing the House of Quality (HoQ) from the Quality Function Deployment methodology. The research employs multiple attribute decision-making techniques, including the Fuzzy Delphi Method, the Fuzzy Analytic Hierarchy Process, and the Compromise Ranking Method. By constructing and analyzing two HoQs, the study identifies key LM practices and DT technologies that serve as critical strategies for advancing SD performance. Finally, with regard to LM practices, no previous research has attempted to conduct a hierarchical classification. This study is the first to construct a hierarchical structure for Just-in-Time and Jidoka.

Keywords: sustainable development; lean management; digital transformation; quality function deployment; multiple attribute decision-making

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1. Introduction

In recent years, the global manufacturing sector has experienced growing pressure to achieve sustainable development (SD) without compromising competitiveness. Enterprises are adopting Lean Management (LM) and Digital Transformation (DT) as essential strategies to improve efficiency, reduce environmental impact, and enhance long-term sustainability. This study aims to explore the interrelationship among SD, LM, and DT, and to develop an integrated analytical framework to better understand how these three dimensions interact within the automotive industry.

1.1. Research Background

Yang et al. [1] pointed out that developing countries heavily rely on petrochemical energy, with the majority of their energy demands met through the combustion of fossil fuels [2]. The excessive use of fossil energy has caused significant harm to the Earth, including the greenhouse effect, extreme weather events, and ecological degradation [3]. As a result, addressing climate change, reducing greenhouse gas (GHG) emissions, managing resource depletion, and mitigating environmental pollution have emerged as some of the most pressing global challenges in recent years [4]. In response, the international community is working toward limiting the rise in global temperatures to no more than 1.5 °C above pre-industrial levels [5]. This effort involves collective commitments to combat climate change, including pledges to cut emissions and adopt advanced technologies for GHG control [6,7]. Governments worldwide are actively developing and implementing policies and programs aimed at achieving these objectives. Akdoğan and Coşkun [8] noted that most enterprises are increasingly emphasizing environmental sustainability, recognizing that SD will become one of the key competitive advantages in the future [9].

Due to above reasons, companies across industries are expanding their investments in sustainability [10], including those in the automotive sector. Lenort et al. [11] emphasized that the automotive industry ranks among the largest global sectors and has recently intensified its investments and implementation of LM and DT practices. Numerous scholars argue that implementing LM can effectively utilize energy and materials, thereby reducing waste [12,13]. Furthermore, researchers have asserted that LM and SD can be seamlessly integrated to eliminate waste and, in turn, enhance competitiveness, resource efficiency, and environmental performance [14,15]. As for DT, George and Schillebeeckx [16] emphasized that digitalization is a key strategy for rapidly achieving SD. Currently, industries are exploring DT as a solution for advancing sustainability, aiming to reach more forward-looking and sustainable business objectives [17]. Amid the wave of DT, the automotive industry is undergoing a transformation unprecedented in the past century [18,19]. However, despite the growing emphasis on sustainability, most existing studies have explored SD, LM, and DT separately. Therefore, this study seeks to explore the interrelationships and combined impacts of these factors, especially within the automotive industry, in order to offer a comprehensive understanding of how LM and DT collectively contribute to SD.

1.2. Research Motivation and Purpose

This study selects the automotive industry as the focus of its research and empirical analysis, given its widely acknowledged status as a leading and representative sector. The industry is often viewed as a key indicator of a nation's industrial and technological development. Furthermore, Lenort et al. [11] pointed out that the automotive industry is regarded as a pillar of the global economy and a significant driver of economic growth, stability, and technological advancement [20]. Additionally, the automotive industry possesses a comprehensive supply chain system with dozens of suppliers [21]. Successful transformation within this sector could bring significant benefits to the overall development of Taiwan's industries.

Moreover, since the automotive industry holds a similarly vital role in numerous economies around the world, the findings of this study may offer valuable insights for other countries aiming to foster sustainable transformation within their manufacturing sectors.

Scholars have confirmed that enterprises successfully implementing LM experience positive effects on the utilization of production resources and the reduction in waste [22,23]. Therefore, sustainability has become a strong partner of LM, and their integration can significantly improve organizational environmental performance. Research on the relationship

between LM and SD is considered a viable strategic approach [24]. Meanwhile, the concept of DT has received substantial attention from governments and industries worldwide over the past decade. Some experts have proposed integrating LM with DT to combine the advantages of traditional LM with digitalization [25,26]. However, some scholars have noted that existing research on the integration of LM and DT primarily concentrates on specific technologies or on performance enhancements resulting from the adoption of individual digital technologies [27,28]. Although some recent studies have made progress in this area, it still remains unclear whether LM methods are directly associated with particular DT technologies [29]. In summary, exploring the relationship among SD, LM, and DT is considered a viable strategy. While the relationships between SD–LM and LM–DT have been discussed individually, this study argues that integrating LM with DT can create a synergistic effect that amplifies the outcomes of SD. Therefore, the proposed SD, LM, and DT framework aims to reveal how the combination of LM principles and DT technologies can jointly accelerate the achievement of sustainability goals, generating benefits greater than those produced by either approach alone.

To achieve this goal, this study first reviews and synthesizes the relevant literature and consults multiple experts to establish various SD indicators, LM methods, and DT technologies in Section 2. Section 3 explains how to apply Quality Function Deployment (QFD) and its House of Quality (HoQ) framework, which embody the systematic and customer-oriented philosophy consistent with LM. QFD provides a structured approach to translating the voice of customers or sustainability needs into technical requirements, aligning well with LM's emphasis on process optimization and waste reduction. Therefore, integrating QFD and HoQ into the analytical framework helps to clarify the relationships among the indicators and supports continuous improvement within the SD, LM, and DT system. Subsequently, two HoQs are constructed to identify the interrelationships among SD, LM, and DT. This study adopts methods from Multiple Attribute Decision Making (MADM), including the Fuzzy Delphi Method (FDM), the Fuzzy Extended Analytic Hierarchy Process (FEAHP), and the VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), to determine which LM methods and DT technologies are key strategies for enhancing corporate SD performance. Section 4 focuses on Taiwan's automotive industry as the empirical case, employing a three-stage expert survey process for data collection and analysis. Lastly, Section 5 offers the study's conclusions and recommendations.

2. Literature Review

2.1. Sustainable Development

In 1987, the World Commission on Environment and Development released the report Our Common Future, commonly referred to as the Brundtland Report. This report has become a foundational reference in environmental science research and has had a profound influence on subsequent developments [30,31]. Since the Earth Summit in Rio de Janeiro in 1992, the concept of SD has become widely embraced, with many countries integrating it into their treaties, constitutions, and legal frameworks. The Brundtland Report highlighted that the fundamental aim of SD is to fulfill the needs of the present generation without jeopardizing the ability of future generations to meet their own needs, emphasizing the importance for businesses to balance economic, social, and environmental goals [32–34]. Traditional business models, which are primarily driven by financial performance, should evolve toward the trend of SD that simultaneously considers social, environmental, and economic impacts [35]. Previous studies on sustainability have shown a strong positive relationship between corporate social responsiveness and profitability [36–38]. Stocchetti [39] pointed out that both academia and industry now recognize that improving sustainable

management and performance represents an opportunity for corporate development and growth, rather than a crisis.

When formulating sustainability policies, enterprises can draw upon the principles of the Triple Bottom Line (TBL) [40]. TBL encompasses three major dimensions: environment, society, and economy [41–43]. Elkington and Rowlands [40] highlighted that the three dimensions of the TBL correspond to people, planet, and profit. The TBL framework evaluates corporate responsibility by assessing how effectively a company meets economic, environmental, and social standards. Vinodh and Girubha [44] and Seuring [45] have applied the TBL framework in their reviews of supply chain management. Govindan et al. [46] combined multi-criteria decision-making (MCDM) with TBL to identify the most sustainable building materials. Hsu et al. [9] utilized QFD and fuzzy MADM to develop key corporate sustainability indicators grounded in TBL principles. Similarly, Liang et al. [47] employed fuzzy MCDM methods based on TBL theory to analyze financing decision models for sustainable supply chains in small and medium-sized enterprises. Similarly, Liu et al. [48] applied MCDM methods based on the TBL framework to identify sustainable suppliers that meet customer requirements. In order to practically assist the automotive industry in developing sustainable business practices, this study consulted two senior managers from the automotive sector, both with over ten years of experience in promoting internal SD initiatives. Based on their practical experience, they suggested three key SD indicators. Additionally, this study reviewed relevant literature and summarized SD indicators related to the economic, social, and environmental dimensions. Table 1 summarizes the literature review of the SD indicators utilized in this study. Beyond the reviewed sources, expert recommendations (as detailed in Reference No. 12) were also incorporated to identify the key SD indicators.

Table 1. Literature review of SD indicators.

Dimension	Indicator	Reference											
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Economy	Reduction in manufacturing costs	●	●	●	●	●	●	●	●	●	●		
	Reduction in procurement costs	●	●	●	●	●				●	●		
	Reduction in transportation costs										●		
	Improvement of service quality		●	●		●	●	●	●	●		●	
	Improvement of product quality	●	●	●	●	●	●	●	●	●	●	●	
	Enhancement of on-time delivery rate	●			●	●	●	●		●	●		
	Reduction in transportation time	●			●	●	●	●	●				
	Enhancement of enterprise innovation	●			●	●							
	Advancement of manufacturing technology				●	●				●	●	●	
	Continuous improvement and reduction in information security risks												●
	Acquisition of relevant information security certifications												●
Society	Reduction in impact on local communities			●	●					●	●		
	Support for community development programs			●	●					●			
	Support for local educational institutions			●	●								
	Increase in local employment opportunities										●	●	
	Reduction in health and accident incidents within the company	●	●	●	●	●	●	●		●			
	Reduction in discrimination incidents within the company			●	●	●							
	Support for employees obtaining job-related professional certifications	●		●	●	●				●	●	●	
	Top management's commitment to sustainable development									●			
	Reduction in employee turnover rate										●		
	Acquisition of relevant labor safety or human rights certifications										●		
	Enhancement of customer health and safety during product use		●	●	●								●
Society	Top management's commitment to sustainable development									●			
	Reduction in employee turnover rate										●		
	Acquisition of relevant labor safety or human rights certifications										●		
	Enhancement of customer health and safety during product use		●	●	●								●
	Increase in channels for communicating product information to customers		●	●	●		●	●					
Environment	Reduction in hazardous substance emissions	●	●		●					●		●	
	Reduction in water pollution	●	●										
	Reduction in land pollution	●	●	●									
	Reduction in air pollution	●	●	●	●						●	●	
	Reduction in greenhouse gas emissions									●	●		
	Reduction in land use			●									
	Reduction in water consumption	●			●					●			
	Reduction in energy consumption	●			●	●							

Table 1. *Cont.*

Dimension	Indicator	Reference											
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Environment	Development of recyclable products		●	●	●		●	●	●	●		●	
	Development of products with lower energy consumption		●	●	●							●	
	Green design						●	●	●		●		
	Green packaging								●				
	Establishment of sustainable supply chains									●			
	Increase in the use of green energy										●	●	
	Acquisition of relevant environmental certifications			●	●	●				●		●	
	Strengthening environmental protection											●	
	Actions to enhance natural resource and environmental protection		●		●	●						●	

(1) Amrina and Yusof [49]; (2) Azadnia et al. [50]; (3) Chardine-Baumann and Botta-Genoulaz [51]; (4) Govindan et al. [52]; (5) Govindan et al. [46]; (6) Mavi et al. [53]; (7) Zarbakhshnia et al. [54]; (8) Prakash and Barua [55]; (9) Cagno et al. [56]; (10) Chang and Cheng [32]; (11) Narwane et al. [57]; (12) Expert recommendations.

2.2. Lean Management

LM has its origins in the Toyota Production System [58,59]. In 1990, Womack and Jones published The Machine That Changed the World, in which they introduced the definition and theory of "Lean" [60]. The term "Lean" in English refers to "having no unnecessary fat but rather being strong and well-toned" [61]. The implementation of LM has had significant and positive impacts across various industries over the past few decades [62]. LM is a structured approach designed to identify and eliminate various forms of waste within a system [63,64].

Many related studies have pointed out that integrating LM with sustainability can generate positive environmental impacts for enterprises [65,66]. For instance, both LM and sustainability focus on reducing waste, shortening delivery times, and utilizing various methods to achieve synergies among personnel, organizations, and supply chain relationships [67]. Viles et al. [68] also highlighted that LM methods have been widely demonstrated to enhance quality and productivity by eliminating operational waste, while simultaneously improving eco-efficiency and reducing organizational environmental risks and impacts. Furthermore, Viles et al. [68] emphasized that many applications of LM methods within production and manufacturing processes have shown positive environmental effects, such as reductions in electricity and water consumption.

Regarding LM methods such as Just in Time (JIT), Jidoka, PDCA, and 5S activities, no previous studies have attempted to establish a hierarchical classification. Previous studies have widely discussed Lean tools; however, few have examined the hierarchical relationships among them. Most research treats JIT and Jidoka as individual improvement methods [69–73]. As a result, the LM methods presented in much of the existing literature are often structured in a single layer. However, this study argues that JIT and Jidoka represent improvement stages or goals and should not be discussed and analyzed at the same level as other methods; a hierarchical structure needs to be established. While traditional LM frameworks, such as the Toyota Production System and Lean Thinking [64,74], have defined JIT and Jidoka as key tools, they have not clearly described their hierarchical interdependence. This study therefore extends the classical Lean structure by redefining these two methods as higher-level improvement stages that integrate and guide other Lean techniques. This conceptual refinement helps address the limitations of tool-based interpretations in previous studies. This is a new concept and attempt proposed by this study. To support this framework, this study consolidated various LM methods from previous scholarly works and consulted two senior managers in the automotive industry, both with over twenty-five years of experience in promoting internal LM initiatives. Based on their industry experience and different perspectives, they recommended nine LM methods and proposed a new dimension called "worksite physical improvement." Table 2 provides an overview of the LM methods identified through the literature review conducted for this study. In addition to the reviewed sources, expert recommendations (as outlined in Ref. [12]) were also considered in selecting the key LM methods.

Table 2. Literature review of LM methods.

Dimension	Indicator	Reference											
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Worksite Physical Improvement	PDCA cycle						●		●	●	●		
	5S Activities	●	●	●	●	●	●	●	●	●	●	●	
	Waster elimination							●		●		●	
	Visual Management	●			●	●	●	●	●	●			
	Cross-Functional Participation				●								
	Standardized Work			●	●	●	●	●	●	●		●	
	Standardized Work Combination Sheet												●
	Production Control Board												●
	Continuous Improvement	●	●			●	●	●	●	●		●	
Just-in-Time	Value Stream Mapping	●	●		●	●	●	●	●	●	●	●	
	Synchronized Operations			●									
	Pull Production	●		●									
	Production Leveling		●	●		●		●	●	●	●		
	Kanban System		●		●	●	●	●	●	●	●		
	Total Quality Management		●					●					
	U-shaped Production Line	●		●	●		●		●	●	●	●	
	Small Lot Production											●	
	Improvement of Mixed-Model Production												●
	Mixed-Load Transport										●		
	High-Frequency Transport												●
Jidoka	Total Productive Maintenance	●	●	●	●	●	●	●	●	●			
	Quick Changeover		●	●	●	●	●	●	●	●	●	●	
	Error-Proofing	●	●	●		●	●		●	●		●	
	Multi-skilled Workers			●									
	Andon System									●	●		
	Passive Mechanical Devices										●		
	Six Sigma	●	●	●			●				●		
	Separation of Man and Machine												●
	Identification of Bottleneck Equipment												●
	Improvement of Equipment Cycle Time Variability												●
	Identification of Equipment Failure Points and Root Causes												●
	Elimination of Non-Loaded Operations												●

(1) Vinodh et al. [75]; (2) Gupta and Kundra [76]; (3) Anvari et al. [69]; (4) Mahapatra and Mohanty [77]; (5) Minh and Kien [78]; (6) Zhou [79]; (7) Kumar et al. [71]; (8) Yadav et al. [80]; (9) Leksic et al. [70]; (10) Bertagnolli et al. [74]; (11) Junior et al. [72]; (12) Expert recommendations.

2.3. Digital Transformation

In recent years, DT has garnered renewed attention with the advent of the Fourth Industrial Revolution. Since the introduction of the term 'Industry 4.0' in 2011, it has become widely acknowledged that the global business landscape is undergoing a profound transformation driven by this new industrial era [81]. Under the context of Industry 4.0, DT has also been newly redefined. With the theoretical foundation of DT becoming increasingly robust, many scholars have engaged in research within this field. Researchers define DT as the process through which organizations leverage digital technologies to develop new business models [82,83], adapt existing processes, and facilitate changes in organizational structures, resources, or relationships with both internal and external stakeholders [84,85].

George and Schillebeeckx [16] pointed out that implementing DT can better advance SD and various industries are actively exploring the use of DT technologies as solutions for achieving SD goals [17]. Singhdong et al. [86] noted that combining DT with sustainability can generate positive environmental impacts for enterprises. For instance, Costa et al. [87] emphasized that various DT technologies—such as cloud computing, Big Data (BD), the Internet of Things (IoT), and artificial intelligence (AI)—can play a significant role in advancing SD within organizations. Similarly, Hrustek [88] illustrated how technologies including BD, IoT, AI, machine learning, blockchain, robotics, and sensor technology (ST) offer valuable contributions to digital agriculture, promoting sustainability through biodiversity adaptation and environmental protection. Furthermore, Ulas [26] identified IoT, robotics, additive manufacturing, AI, augmented and virtual reality, and ST as the most widely adopted DT technologies. Moreover, other scholars have supplemented this list by identifying additional DT technologies, including human–machine collaboration, monitoring and data acquisition, real-time locating systems, smart grids, fifth-generation mobile communications, product cloud services, and simultaneous localization and mapping [89–95].

More recently, Shen [96] conducted a meta-analysis of empirical research on DT, innovation, and firm performance, revealing generally positive effects and highlighting significant country-specific moderating factors [97]. Slavković et al. [98] examined the role of digital citizenship and DT enablers, showing that they positively influence firms' innovativeness and problem-solving capabilities [99]. In addition, Saini and Kharb [100] analyzed the Digital India initiative, highlighting how large-scale DT programs can empower SD through infrastructure, policy, and capability building [101]. These recent contributions provide further justification for linking DT technologies to SD outcomes and reinforce the rationale of this study.

Kim et al. [97] classified the previously mentioned DT technologies into four key dimensions: digital infrastructure, digital platforms, digital applications, and digital services. Building on this framework, Kao et al. [99] further refined these dimensions into six categories: infrastructure, value data, organizational operations, production process optimization, customer relationships, and business models.

Numerous studies on DT have identified commonly used enterprise programs and software, including Enterprise Resource Planning, Product Lifecycle Management, Computer-Aided Design (CAD), Computer-Aided Manufacturing, Manufacturing Execution Systems, and Customer Relationship Management (CRM) [26,91,101,102]. However, with growing emphasis on sustainability in recent years, researchers have increasingly focused on digital tools that integrate DT with sustainability objectives—such as Carbon Footprint Management Systems, Energy Management Systems, and Information Security Management Systems [103–105].

In summary, how to integrate the research on the interrelationships between key DT technologies and LM methods, and thereby identify critical strategies for enhancing corporate SD performance, is a topic worthy of investigation.

3. Research Method

3.1. Research Framework

This section outlines the research methods and procedures employed within the HoQ framework. As the primary aim of this study is to integrate the three previously mentioned elements using the HoQ, and to perform both correlation assessments and interrelationship analyses among them, two separate HoQ frameworks were developed, as illustrated in Figure 1.

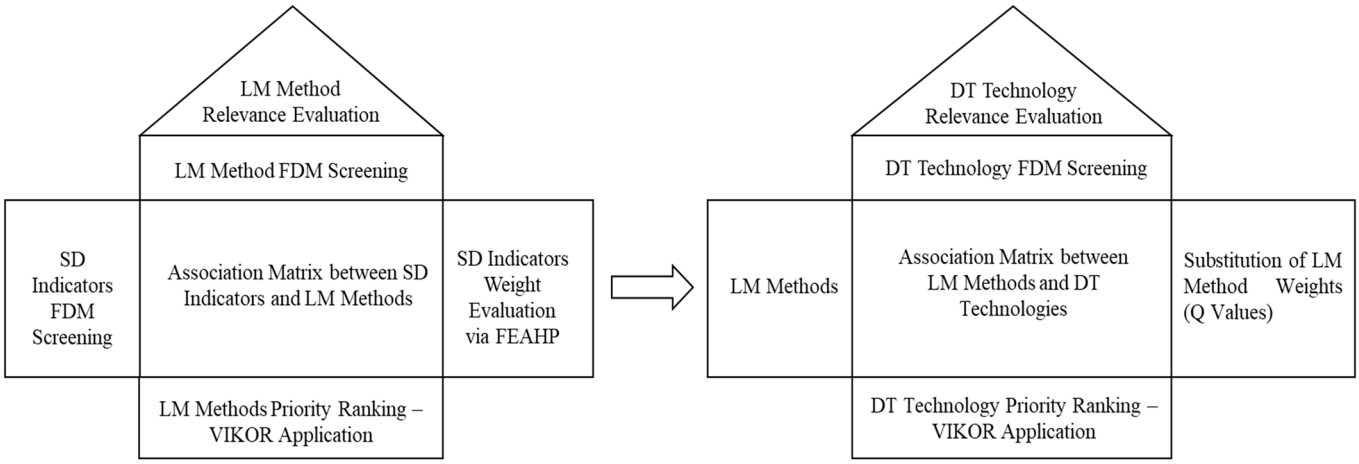


Figure 1. Two HoQ frameworks proposed in this study. Source: Compiled by this study.

This study integrates FDM, HoQ, FEAHP, and VIKOR to propose a quantitative evaluation model. First, SD indicators, LM methods, and DT technologies are defined. Then, FDM is employed to filter the key SD indicators, LM methods, and DT technologies. Subsequently, the SD indicators and LM methods are analyzed using the HoQ within QFD, forming the first HoQ framework. The weights of the SD indicators are calculated through FEAHP and combined with the VIKOR method to prioritize the LM methods. Next, the LM methods and DT technologies are analyzed using another HoQ within QFD, forming the second HoQ framework. The VIKOR method is then applied to prioritize the DT technologies. Finally, the decision sequence for identifying the key LM methods and DT technologies that can enhance corporate SD performance is established.

In this study, the FDM, FEAHP, and VIKOR were sequentially employed within the HoQ framework to establish and analyse the interrelationships among SD, LM, and DT. The FDM was adopted instead of the classical Delphi method because it can effectively handle linguistic ambiguity and uncertain expert opinions, accelerating the consensus process [106,107]. The FEAHP was selected rather than fuzzy Technique for Order Preference by Similarity to Ideal Solution, Decision-Making Trial and Evaluation Laboratory (DEMATEL), or Analytic Network Process (ANP), as it provides a stable hierarchical weighting structure suitable for multi-level criteria, whereas DEMATEL or ANP are more appropriate for networked relationships [108–110]. For prioritisation, the VIKOR method was chosen over Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) because it focuses on compromise solutions and can effectively rank alternatives with conflicting objectives [111]. Finally, HoQ was employed as it allows the visual mapping of relationships between

indicators and strategies, making the analytical results more interpretable for industrial practitioners [112–114].

3.2. The Fuzzy Delphi Method

To improve clarity for non-specialist readers, the overall process of the FDM used in this study can be summarized as follows. First, an expert panel composed of scholars and experienced industry practitioners is established. Each expert evaluates the importance of candidate items using a range of values to express their subjective judgments. Second, the collected expert opinions are transformed into fuzzy numbers to represent both optimistic and conservative viewpoints. Third, statistical aggregation is applied to filter inconsistent responses, after which the consensus level (G^i) is calculated. Finally, items that meet the consensus threshold are retained for further analysis. This stepwise procedure ensures that expert opinions are objectively integrated while maintaining methodological transparency.

Ishikawa et al. [106] applied the principles of fuzzy theory to enhance the Delphi method, proposing two distinct approaches: the cumulative frequency distribution method using max-min values, and the fuzzy integral method. Expert opinions were synthesized through a fuzzy number process known as the FDM. The procedure consists of the following steps:

Step 1: To validate the evaluation criteria, the researcher assembles a panel of experts comprising academic scholars and industry professionals from relevant fields. These experts are asked to assign an interval of values that reflects the perceived importance of each evaluation criterion. Within this interval, the "minimum value" denotes the expert's most conservative assessment, while the "maximum value" represents the most optimistic assessment.

Step 2: Once the expert questionnaires are collected and compiled, the researcher removes outlier responses—specifically, those falling beyond two standard deviations from the extreme values. The minimum value, geometric mean, and maximum value are then calculated for both the most conservative and most optimistic assessments. Accordingly, for each evaluation item i, two triangular fuzzy numbers are derived: one for the most conservative assessment, denoted as $C^i = (C_L^i, C_M^i, C_U^i)$, and one for the most optimistic assessment, denoted as $O^i = (O_L^i, O_M^i, O_U^i)$, as illustrated in Figure 2.

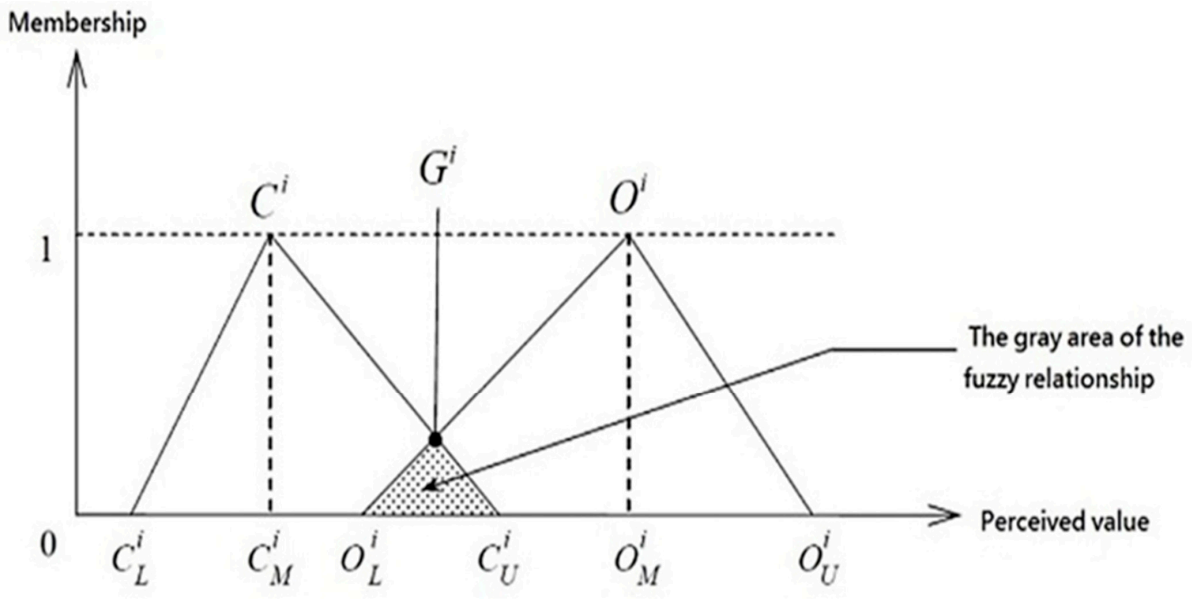


Figure 2. Grey area of fuzzy relations.

Step 3: The researcher calculates the degree of consensus, denoted as G^i, which represents the consensus value of importance for each evaluation item. The calculation of G^i is based on the following three conditions:

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

$$G^i = \left(C_M^i + O_M^i\right)/2 \tag{1}$$

2. If two triangular fuzzy numbers overlap, then ($C_U^i > O_L^i$) and $Z^i < M^i$, where $Z^i = O_M^i - C_M^i$, which represents that the grey area of the fuzzy relationships is smaller than the experts' interval $\left(M^i = O_M^i - C_M^i\right)$ of the evaluation item's "geometric mean of optimistic cognition" and "geometric mean of the conservative cognition." Although the interval values of expert opinions do not overlap—indicating no direct consensus—the divergence between the most extreme opinions and those of other experts is not substantial. In such cases, the importance consensus value for evaluation item i is calculated using Equation (2) [9,115].

$$G^i = \frac{\left[\left(C_U^i \times O_M^i\right) - \left(O_L^i \times C_M^i\right)\right]}{\left[\left(C_U^i - C_M^i\right) + \left(O_M^i - O_L^i\right)\right]} \tag{2}$$

3. If the two triangular fuzzy numbers overlap—that is, when ($C_U^i > O_L^i$) and $Z^i = O_M^i - C_M^i$, this indicates that the experts' interval values lack a segment of consensus. In other words, the range of expert opinions is too divergent to reflect agreement. Consequently, such evaluation items are considered non-convergent. These items should be returned to the expert panel for further review through an additional round of the questionnaire process, until consensus is reached and a definitive importance consensus value can be established.

3.3. The Fuzzy Logic

Zadeh [116] introduced fuzzy set theory as a means to address uncertainty in the representation of vague or imprecise events. In a fuzzy set, each element can possess a degree of membership ranging from 0 to 1, allowing for partial inclusion. Furthermore, a fuzzy set can incorporate an infinite number of membership functions. As a result, fuzzy sets offer greater flexibility and are more appropriate than classical sets for analyzing complex, nonlinear systems commonly encountered in real-world scenarios.

Fuzzy logic often involves the uses of semantic variables. Common semantic variables include triangular, trapezoidal, and Gaussian fuzzy numbers. In fuzzy logic, specific semantic evaluations are used to define corresponding membership functions. Semantic variables, which can be used as a basis for thinking and making judgments, are based on words or texts in natural languages rather than data. Triangular fuzzy numbers, as shown in Figure 3, are denoted by $\widetilde{\mu} = (a, b, c)$, where $a \leq b \leq c$, and $a \geq 0$ for μ to be a positive triangular fuzzy number.

If two triangular fuzzy numbers $\tilde{A} = (a_1, b_1, c_1)$ and $\widetilde{B} = (a_2, b_2, c_2)$ exist and the fuzzy values

$$\begin{aligned} \text{Addition}: \quad & +\widetilde{B} = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \\ \text{Subtraction}: \quad & -\widetilde{B} = (a_1 - c_2, b_1 - b_2, c_1 - a_2) \\ \text{Multiplication}: \quad & \times\widetilde{B} = (a_1 \times a_2, b_1 \times b_2, c_1 \times c_2) \\ \text{Division}: \quad & \div\widetilde{B} = (a_1 \div c_2, b_1 \div b_2, c_1 \div a_2) \end{aligned} \tag{3}$$

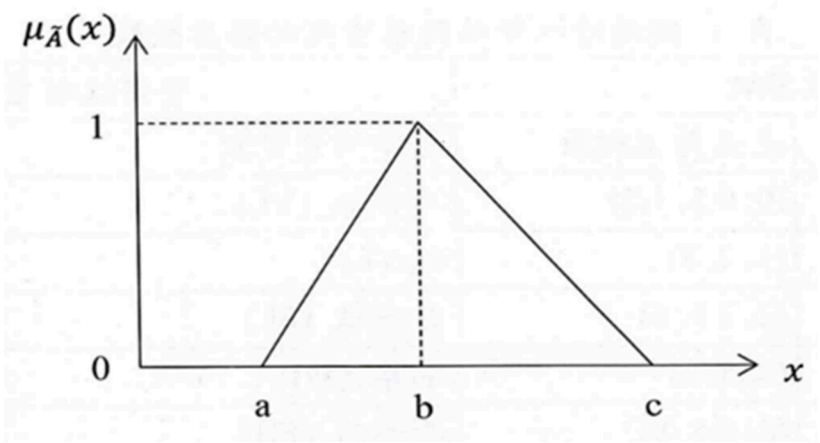


Figure 3. Triangular fuzzy number.

3.4. The Fuzzy Extended Analytical Hierarchy Process

Chang [109,110] proposed the FEAHP, a method that has been widely adopted in subsequent research due to its straightforward implementation. The steps and procedures of FEAHP are outlined as follows:

Suppose that $X = \{x_1,\ x_2, x_3, \ldots, x_n\}$ is the object set, and G $= \{g_1, g_2, g_3, \ldots, g_n\}$ is the goal set. According to Chang's extent analysis method [109,110], each alternative is evaluated with respect to each criterion through extent analysis. Fuzzy numbers are employed to quantify the degree of satisfaction or preference. As a result, each alternative obtains m extent values corresponding to m criteria, expressed as follows:

$$M_{gi}^{1}, M_{gi}^{2}, \ldots, M_{gi}^{m},\ i = 1, 2, \ldots, n \tag{4}$$

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

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

$$S_i = \sum_{j=1}^{m} M_{gi}^{j} \odot \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right]^{-1} \tag{5}$$

where $\sum_{j=1}^{m} M_{gi}^{j}$ represents the fuzzy summation of the m extent analysis values.

$$\sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j \right) \tag{6}$$

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

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right] = \left(\sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i \right) \tag{7}$$

Then the vector inverse matrix of Equation (5) is calculated as follows:

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i} \right) \tag{8}$$

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:

$$V_{(M_2 \geq M_1)} = sup_{y \geq x}\left[min\left(\mu_{M1}{}^{(x)}, \mu_{M2}{}^{(y)}\right)\right] \tag{9}$$

$$V_{(M_2 \geq M_1)} = hgt_{(M_1 \cap M_2) = \mu_{M2}{}^{(d)}} = \begin{bmatrix} 1, & \text{if } m_2 > m_1 \\ 0, & \text{if } l_1 \geq u_2 \\ \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & \text{otherwise,} \end{bmatrix} \tag{10}$$

where the value d represents the projection of point D onto the X-axis. Point D is the highest point of intersection between the two membership functions M_1 and M_2 (see Figure 4).

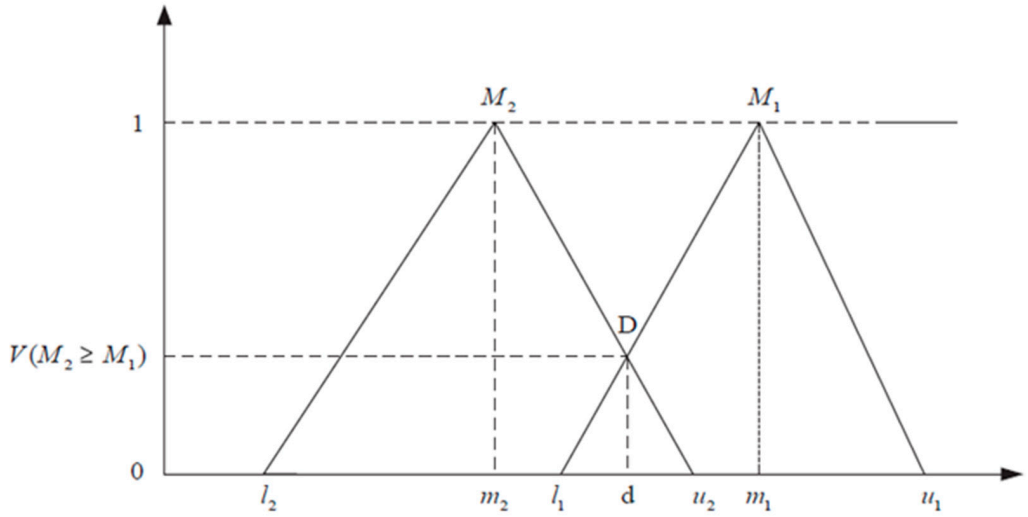


Figure 4. The intersection of the triangular fuzzy numbers M_1 and M_2.

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 simultaneously, as they are interdependent.

Step 3: A convex fuzzy number is considered greater than the other k convex fuzzy numbers based on the degree of possibility. $M_i (i = 1, 2, \ldots, k)$, defined as follows: $V_{(M \geq M_1, M_2, \ldots, M_k)} = V_{[(M \geq M_1), (M \geq M_2), \ldots, (M \geq M_k)]} = minV_{(M \geq M_i),\ i=1\ldots,k}$

If

$$d'(A_i) = minV_{(S_i \geq S_k)} \tag{11}$$

where $k = 1, 2, \ldots, n; k \neq i$. The resulting weight vector is then defined as:

$$W' = \left(d'(A_1), d'(A_2), \ldots, d'(A_n)\right)^T, \tag{12}$$

where $A_1 (i = 1, 2, \ldots n)$ represents a set of n elements.

Step 4: The normalized weight vector is denoted as

$$W = (d(A_1), d(A_2), \ldots, d(A_n))^T \tag{13}$$

Step 5: Hierarchical Aggregation. Following the previous calculations, the weight assigned to each criterion reflects its relative importance only within its respective level of the hierarchy. To establish the overall priority of each criterion across the entire hierarchical structure, hierarchical aggregation is required. The formula used for hierarchical weight aggregation is as follows:

$$W_{kp} = NW_k \otimes NW_p \tag{14}$$

where

- NW_k denotes the weight of the second-level dimension.
- NW_p denotes the weight of the third-level criterion.
- NW_{kp} represents the overall weight obtained by multiplying the second-level and third-level weights.

Step 6: Fuzzy Consistency Test, During the FEAHP weighting process, inconsistencies may arise in the pairwise comparisons made by decision-makers regarding the relative importance of the decision factors. Therefore, it is necessary to perform a consistency test on the fuzzy pairwise comparison matrix to ensure the coherence of the judgments. Buckley [108] suggested that the consistency of a fuzzy pairwise matrix can be tested using the consistency verification method originally proposed by Saaty [117] in Analytic Hierarchy Process.

If the consistency ratio (C.R.) exceeds 0.1, the inconsistency of the matrix is deemed unacceptable, requiring decision-makers to reassess the relative importance of the factors. According to Saaty [118], a C.R. value of 0.1 or below is considered acceptable for subjective evaluations among criteria.

The consistency ratio is calculated using the following formula:

$$C.R. = \frac{C.I.}{R.I.}, \; C.I. = \frac{\lambda_{\max} - n}{n - 1} \tag{15}$$

where $\lambda_{\max}$ is the maximum eigenvalue of the fuzzy comparison matrix, and n represents the number of criteria.

3.5. The Quality Function Deployment

The concept and application of QFD were introduced by Japanese scholars Yoji Akao and Shigeru Mizuno in the 1960s. Its primary purpose is to translate customer needs into technical requirements throughout the product development and manufacturing processes [112]. As a customer-focused engineering methodology, QFD has been demonstrated to be an effective tool for enhancing product design and quality. In recent years, the use of QFD has expanded beyond product development and design to include areas such as design planning, engineering, strategic development, as well as supplier evaluation and selection [113,114]. QFD has become one of the most commonly used tools for solving MADM and MCDM problems, and it has been applied across various fields.

This study employs QFD to construct two HoQ. The detailed structure of the first HoQ, as illustrated in Figure 5, establishes a systematic framework for analyzing the relationship between SD and LM. The analytical steps and procedures are as follows:

Step 1: Selection of SD Indicators: Relevant SD indicators were first compiled through a comprehensive literature review. Subsequently, expert opinions from related fields were gathered through interviews to design the FDM questionnaire. Based on the experts' evaluations and iterative discussions, FDM calculations were conducted, and a threshold value was set to screen and retain the most important SD indicators.

Step 2: Determining the Weights of SD Indicators (W_1). A questionnaire survey using fuzzy linguistic evaluations was conducted to analyze the importance of individual SD indicators. The FEAHP was then applied to calculate the importance matrix of the SD indicators, denoted as W_1. In the W_1 matrix, each W_i represents the weight of an individual SD indicator, $i = 1, 2, \ldots n$.

Step 3: Selection of LM Methods. Relevant LM methods were compiled through an extensive literature review. Expert opinions from related fields were then gathered through interviews to design the FDM questionnaire. Based on expert input and iterative discussions, FDM calculations were conducted, and a threshold value was established to identify and retain the most significant LM methods.

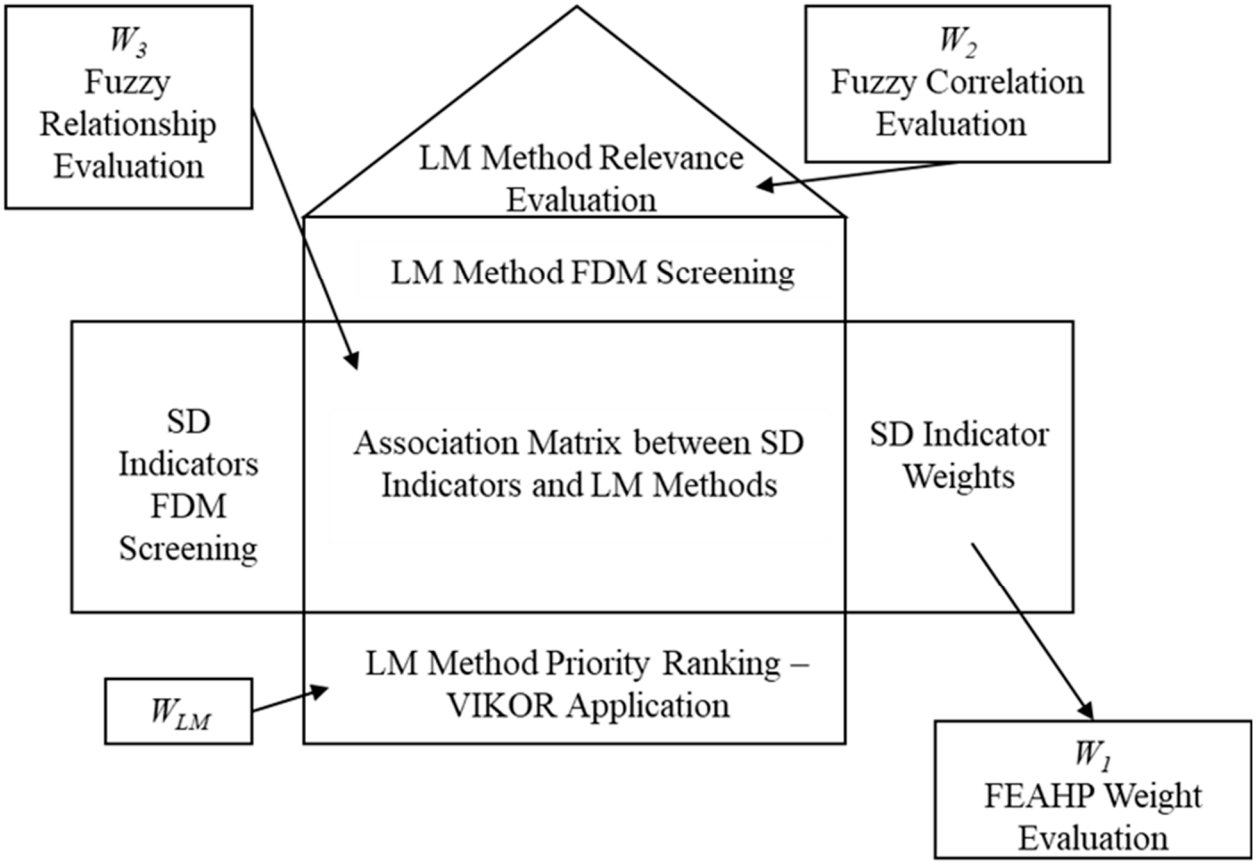


Figure 5. The first house of quality framework in this illustration.

Step 4: Constructing the LM Correlation Matrix (W_2). It determines the interrelationships among the selected LM methods. This step aimed to identify whether the LM methods were complementary or conflicting. The assessment was conducted based on evaluations provided by experts in relevant fields.

Step 5: Constructing the Relationship Matrix Between SD Indicators and LM Methods (W_3). It was constructed to explore the interrelationships between each SD indicator and LM method. Experts and scholars from relevant fields were invited to assess the degree of association between the two sets of elements.

Step 6: Calculating the Integrated Relationship Matrix Between SD Indicators and LM Methods (W_{LM}). It was derived by combining the LM correlation matrix (W_2) with the relationship matrix between SD indicators and LM methods (W_3). Using Equation (16), the integrated matrix (W_{LM}) was calculated to reflect the comprehensive relationships between the two sets of elements.

$$W_{LM} = W_2 \otimes W_3 \tag{16}$$

Step 7: Determining the Priority Ranking of LM Methods (W_{LM}). By integrating QFD with the VIKOR method, the degree of relationship between SD indicators and LM methods was assessed to determine the priority ranking of the LM methods. Based on the results, recommendations for the application of LM methods were developed to guide decision-makers in the automotive industry.

The detailed configuration of the second HoQ is depicted in Figure 6, which establishes a systematic framework for analyzing the relationship between LM methods and DT. The analytical steps and procedures are as follows:

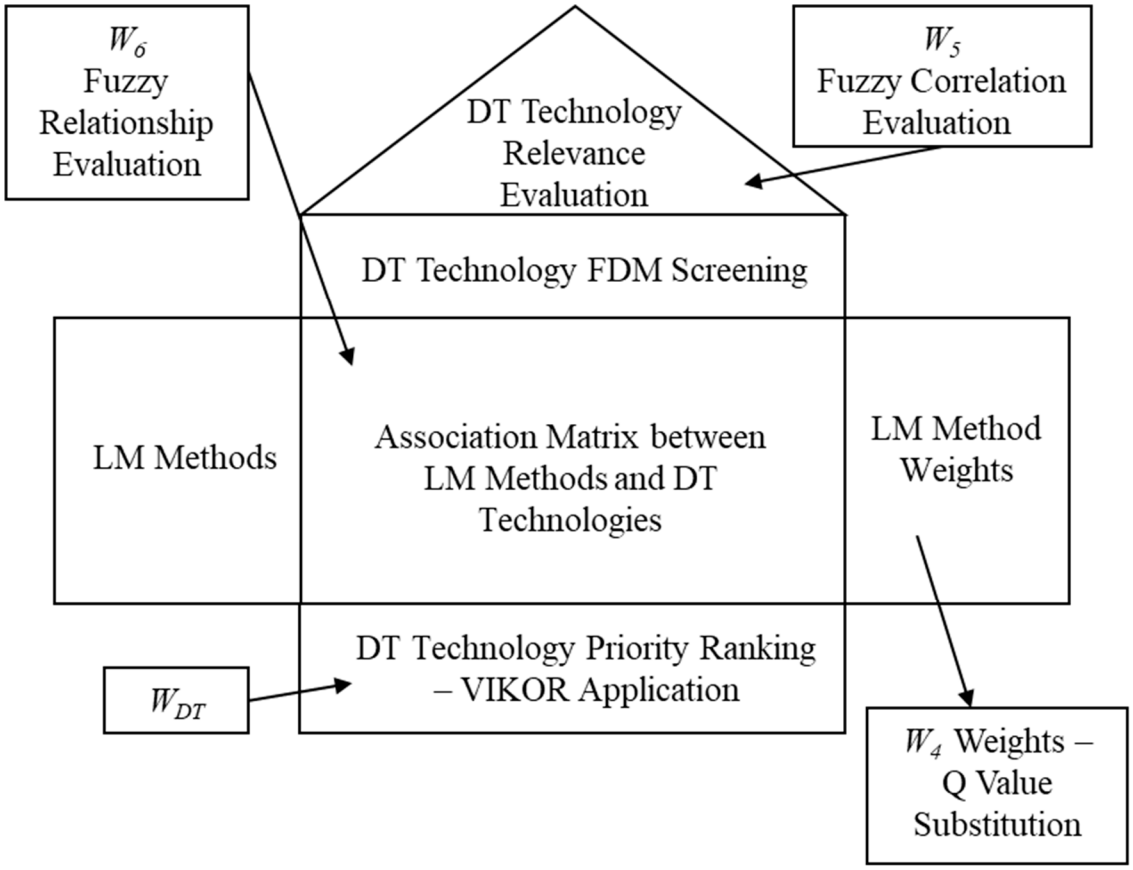


Figure 6. The second house of quality framework in this study.

Step 1: The importance levels of LM methods (performance values Q_j) obtained from the first HoQ are carried over and used to construct the LM importance matrix (W_4) in the second HoQ.

Step 2: Selection of DT Technologies: Relevant DT technologies were compiled from the literature. Expert interviews were then conducted to design the FDM questionnaire. Based on the experts' input and iterative discussions, FDM calculations were performed, and a threshold value was set to screen for the most important DT technologies.

Establish the DT Technology Correlation Matrix (W_5), determine the correlation among various DT technologies, and identify whether there are synergies or conflicts among them. The evaluation is conducted by experts in the relevant fields.

Step 3: Construct the Association Matrix between LM Methods and DT Technologies (W_6) to explore the interrelationships between each LM method and DT technology. Experts and scholars from relevant fields are invited to evaluate the degree of association.

Step 4: Derive the Integrated Association Matrix between LM Methods and DT Technologies (W_{DT}) by combining the DT Technology Correlation Matrix (W_5) and the Association Matrix between LM Methods and DT Technologies (W_6). The integrated matrix (W_{DT}) is obtained using Equation (17).

$$W_{DT} = W_5 \otimes W_6 \tag{17}$$

Step 5: Determine the Priority Order of DT Technologies (W_{DT}) through the application of QFD combined with the VIKOR method. This process identifies the degree of association between LM methods and DT technologies, leading to the ranking of DT technologies. Recommendations for the application of DT technologies are then proposed to act as a reference to stakeholders within the automotive sector.

3.6. The VlseKriterijuska Optimizacija I Komoromisno Resenje

The VIKOR approach was introduced to overcome the limitations of the TOPSIS [119]. Developed by Opricovic in 1998, VIKOR is a MCDM approach specifically designed to address discrete decision problems characterized by conflicting and incomparable criteria [111]. The fundamental concept of the VIKOR method lies in the trade-off and compromise between the Positive Ideal Solution (PIS) and the Negative Ideal Solution (NIS). The PIS denotes the optimal value across the evaluation criteria, whereas the NIS represents the least favorable value. Each alternative is subsequently assessed according to its proximity to the ideal solution, with smaller deviations corresponding to higher priority in the ranking. The following steps are undertaken:

Step 1: Construct the initial evaluation matrix. The initial evaluation matrix is obtained by integrating the correlation matrix (W_{LM}) using the first HoQ Formula (14) and the correlation matrix (W_{DT}) using the second HoQ Formula (15).

Step 2: Establish the positive and negative ideal solutions.

$$f_i^* = \left[\left\langle max_j X_{ij}\right\rangle | i \in I_1 | \right\rangle, \left\langle min_j x_{ij} | i \in I_2 | \right\rangle] \forall_i \tag{18}$$

$$f_i^- = \left[\left\langle max_j X_{ij}\right\rangle | i \in I_1 | \right\rangle, \left\langle min_j x_{ij} | i \in I_2 | \right\rangle] \forall_i \tag{19}$$

In the formula above, j denotes the alternative, i represents the evaluation criterion, and X_{ij} is the performance evaluation value of the alternative obtained from the questionnaire. The set I_1 comprises benefit criteria, while I_2 includes cost criteria. Additionally, f_i^* corresponds to the PIS and f_i^- NIS, respectively.

Step 3: Standardize the raw matrix data. The initial matrix data x_{ij} is referred to as r_{ij} upon standardization.

$$r_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{s} X_{ij}^2}}, 1 \leq \mathrm{i} \leq \mathrm{m}, 1 \leq \mathrm{j} \leq \mathrm{n}, \mathrm{uij} \in \mathrm{B} \tag{20}$$

Step 4: Calculate group utility S_j and individual regret R_j

$$S_j = \sum_{i=1}^{m} w_i \left(f_i^* - X_{ij}\right) / \left(f_i^* - f_i^-\right) \forall_i \tag{21}$$

$$R_j = MAX_i \left[w_i \left(f_i^* - X_{ij}\right) / \left(f_i^* - f_i^-\right)\right] \forall_i \tag{22}$$

In Formulas (24) and (25), it should be noted that the standardized weight values derived from FEAHP in the first stage are applied as the weights for the initial stage of the HoQ. Subsequently, the results obtained from the first stage of the HoQ are utilized as the weights for the second stage of the HoQ.

Step 5: Calculate the sorting values Q_j

$$\begin{gathered} Q_j = V\left(S_j - S^*\right) / \left(S^- - S^*\right) + (1 - V)\left(R_j - R^*\right) / \left(R^- - R^*\right) \\ S^* = Min_J S_j;\ S^- = Max_j S_j;\ R^* = Min_j R_j;\ R^- = Max_j R_j \end{gathered} \tag{23}$$

In Formula (26), the weight of the strategy representing "the majority of criteria" (or the maximum group utility) is denoted, where V = 0.5. This compromise solution is considered stable within the decision-making process. However, decision-makers may select different values of v for the calculation based on their individual preferences. Q_j denotes VIKOR index.

4. Empirical Research

A total of 24 respondents participated in the first-stage questionnaire, all of whom held positions at the director or section chief level, with 17 possessing over 20 years of professional experience. For the subsequent second and third stages, 10 experts will be selected from these 17 highly experienced respondents to complete the following questionnaires. Taiwan's automotive industry currently includes six major domestic vehicle manufacturers. Each manufacturer is supported by approximately 40–50 first-tier component suppliers, in addition to numerous second- and third-tier suppliers. This extensive multi-tier supply chain reflects both the scale and complexity of the sector, and it also underscores the representativeness of the selected respondents.

This study segmented the questionnaire process into three stages. In the first stage, an FDM expert questionnaire was employed to screen key SD indicators, LM methods, and DT technologies. A total of 30 questionnaires were distributed, with 24 completed and returned, yielding a response rate of 80%. The second stage involved the design of three distinct types of questionnaires: (1) evaluation of the importance of SD indicators, (2) assessment of correlations among LM methods, and (3) assessment of correlations between SD indicators and LM methods. Ten questionnaires were distributed in this stage, all of which were returned, resulting in a 100% response rate. The third stage comprised two types of questionnaires: (1) assessment of correlations among DT technologies, and (2) assessment of correlations between LM methods and DT technologies. Similarly, 10 questionnaires were distributed and all were collected, again achieving a 100% response rate.

4.1. Findings Derived from the Fuzzy Delphi Method

To screen the SD indicators, LM methods, and DT technologies, Equations (1) and (2) were employed to calculate the agreed-upon importance value (G_i) for each item, as presented in Tables 3–5. The threshold for SD indicators was set at $G^i > 8.25$, reducing the original 40 items to 24. For LM methods, the threshold was set at $G^i > 7.50$, reducing the original 32 items to 20. For DT technologies, the threshold was set at $G^i > 7.20$, resulting in a reduction from 26 to 17 items. Based on the literature, most scholars adopt the TBL perspective proposed by Elkington and Rowlands [40] when evaluating SD indicators. Therefore, this study also adopts the three primary dimensions: economic, social, and environmental—as its foundation. These dimensions are coded as (EC), (SC), and (EN), respectively, for subsequent FEAHP weight calculation. As for the LM methods and DT technologies, they are denoted as (LM) and (DT), respectively.

The consensus threshold ($G^i > 8.25$, $G^i > 7.50$, $G^i > 7.20$) was determined through group discussion and unanimous agreement among the 24 participating experts, all of whom held managerial-level positions or above. During the evaluation meeting, the experts collectively reviewed the distribution of the initial questionnaire results and agreed that a threshold value of 8.25 would sufficiently represent a strong consensus level for this study. This process ensured that the threshold was established based on professional judgment and practical experience, thereby enhancing both the methodological rigor and contextual reliability of the results.

Table 3. Fuzzy Delphi results and codes for sustainable development indicators.

Dimension	Indicator	Code	Degree of Importance of Consensus G^i
Economy	Reduction in manufacturing costs	EC01	8.57
	Reduction in procurement costs	EC02	8.64
	Reduction in transportation costs	EC03	8.53
	Improvement of service quality	EC04	8.61
	Improvement of product quality	EC05	8.84
	Enhancement of on-time delivery rate	EC06	8.93
	Reduction in transportation time	EC07	8.73
	Advancement of manufacturing technology	EC08	8.51
	Continuous improvement and reduction in information security risks	EC09	8.40
Society	Reduction in health and accident incidents within the company	SC01	8.84
	Reduction in discrimination incidents within the company	SC02	9.28
	Support for employees obtaining job-related professional certifications	SC03	8.46
	Top management's commitment to sustainable development	SC04	8.56
	Reduction in employee turnover rate	SC05	8.71
	Acquisition of relevant labor safety or human rights certifications	SC06	8.43
	Enhancement of customer health and safety during product use	SC07	8.57
	Increase in channels for communicating product information to customers	SC08	8.27
Environment	Reduction in hazardous substance emissions	EN01	8.81
	Reduction in water pollution	EN02	8.56
	Reduction in land pollution	EN03	8.78
	Reduction in air pollution	EN04	8.84
	Reduction in greenhouse gas emissions	EN05	8.77
	Establishment of sustainable supply chains	EN06	8.33
	Acquisition of relevant environmental certifications	EN07	8.36

Table 4. Fuzzy Delphi results and codes for lean management methods.

Dimension	Method	Code	Degree of Im-portance of Con-sensus G^i
Worksite Physical Improvement	PDCA cycle	LM01	7.89
	5S Activities	LM02	8.73
	Waster elimination	LM03	8.71
	Visual Management	LM04	8.00
	Cross-Functional Participation	LM05	7.58
	Standardized Work	LM06	9.05
	Standardized Work Combination Sheet	LM07	7.82
	Production Control Board	LM08	8.12
	Continuous Improvement	LM09	8.76
Just-in-Time	Pull Production	LM10	7.55
	Production Leveling	LM11	7.68
	Kanban System	LM12	7.57
	Total Quality Management	LM13	8.59
	Total Quality Management	LM14	7.56
Jidoka	Total Productive Maintenance	LM15	7.72
	Error-Proofing	LM16	9.72
	Multi-skilled Workers	LM17	7.67
	Andon System	LM18	7.76
	Identification of Equipment Failure Points and Root Causes	LM19	8.14
	Elimination of Non-Loaded Operations	LM20	7.89

Table 5. Fuzzy Delphi results and codes for digital transformation technologies.

Dimension	Technology	Code	Degree of Im-portance of Con-sensus G^i
Infrastructure and Platform	Enterprise Resource Planning	DT01	7.52
	Information Security Management System	DT02	7.79
	Product Lifecycle Management	DT03	7.50
	Computer-Aided Design	DT04	7.29
	Computer-Aided Manufacturing	DT05	7.88
	Carbon Management System Platform	DT06	7.28
	Energy Management System	DT07	7.22
Smart Manufacturing and Production Optimization	Internet of Things	DT08	7.79
	Manufacturing Execution System	DT09	7.35
	Robotics, e.g., autonomous and collaborative	DT10	7.31
	Human–Robot Collaboration	DT11	7.27
Data Analytics and Intelligent Decision-Making	Big Data Analytics	DT12	7.65
	Customer Relationship Management	DT13	7.55
	Smart Grid	DT14	7.28
Cloud and Network Connectivity	Cloud Computing	DT15	7.26
	Supervisory Control and Data Acquisition	DT16	7.21
	Sensor Technology	DT17	8.12

4.2. Results of the Fuzzy Extended Analytic Hierarchy Process

Based on the literature, most scholars applying fuzzy logic in their studies adopt triangular fuzzy numbers for evaluation [120,121]. Therefore, this study also uses triangular fuzzy numbers as the foundation for subsequent FEAHP weight calculation.

Next, pairwise comparisons were conducted using Equation (4) to assess the relative importance among variables and to construct fuzzy pairwise comparison matrices. Ten experts were invited to perform fuzzy pairwise comparisons for the three main dimensions of SD, as shown in Table 6. Subsequently, fuzzy pairwise comparisons were conducted for the respective indicators within the EC, SC, and EN dimensions. Due to space limitations, only the results of the fuzzy pairwise comparisons among the main dimensions are presented here. Since the process for indicator-level comparisons mirrors that of the dimensions, detailed results for indicators are omitted. Finally, using the fuzzy logic formulation in Equation (3) and FEAHP Equations (5) and (7), the fuzzy synthetic extent values for both dimensions and indicators were calculated.

Table 6. Fuzzy pairwise comparison matrix for sustainable development dimensions.

	Expert	EC	SC	EN
EC	1	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)
	2	(1.00, 1.00, 1.00)	(1/3, 1/2, 1.00)	(1/4, 1/3, 1/2)
	3	(1.00, 1.00, 1.00)	(1.00, 2.00, 3.00)	(1/3, 1/2, 1.00)
	4	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)	(1.00, 2.00, 3.00)
	5	(1.00, 1.00, 1.00)	(1.00, 2.00, 3.00)	(1.00, 2.00, 3.00)
	6	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)	(1.00, 2.00, 3.00)
	7	(1.00, 1.00, 1.00)	(6.00, 7.00, 8.00)	(1.00, 2.00, 3.00)
	8	(1.00, 1.00, 1.00)	(1.00, 2.00, 3.00)	(2.00, 3.00, 4.00)
	9	(1.00, 1.00, 1.00)	(2.00, 3.00, 4.00)	(2.00, 3.00, 4.00)
	10	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)	(1.00, 2.00, 3.00)

Table 6. *Cont.*

	Expert	EC	SC	EN
SC	1	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)	(1.00, 2.00, 3.00)
	2	(1.00, 2.00, 3.00)	(1.00, 1.00, 1.00)	(1/4, 1/3, 1/2)
	3	(1/3, 1/2, 1.00)	(1.00, 1.00, 1.00)	(1/3, 1/2, 1.00)
	4	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)
	5	(1/3, 1/2, 1.00)	(1.00, 1.00, 1.00)	(1.00, 2.00, 3.00)
	6	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)
	7	(1/8, 1/7, 1/6)	(1.00, 1.00, 1.00)	(1/9, 1/9, 1/9)
	8	(1/3, 1/2, 1.00)	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)
	9	(1/4, 1/3, 1/2)	(1.00, 1.00, 1.00)	(1.00, 2.00, 3.00)
	10	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)
EN	1	(1.00, 1.00, 1.00)	(1/3, 1/2, 1.00)	(1.00, 1.00, 1.00)
	2	(2.00, 3.00, 4.00)	(2.00, 3.00, 4.00)	(1.00, 1.00, 1.00)
	3	(1.00, 2.00, 3.00)	(1.00, 2.00, 3.00)	(1.00, 1.00, 1.00)
	4	(1/3, 1/2, 1.00)	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)
	5	(1/3, 1/2, 1.00)	(1/3, 1/2, 1.00)	(1.00, 1.00, 1.00)
	6	(1/3, 1/2, 1.00)	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)
	7	(1/3, 1/2, 1.00)	(9.00, 9.00, 9.00)	(1.00, 1.00, 1.00)
	8	(1/4, 1/3, 1/2)	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)
	9	(1/4, 1/3, 1/2)	(1/3, 1/2, 1.00)	(1.00, 1.00, 1.00)
	10	(1/3, 1/2, 1.00)	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)

The fuzzy comprehensive values for the dimensions and corresponding criteria were first calculated using Equation (8). Subsequently, Equations (9) and (10) were employed to perform the comparison of $M_2 \geq M_1$, deriving the degree of possibility. Equation (11) was then used to determine the minimum values (minV) for both the dimensions and individual criteria. Following this, the weighted values (W') and normalised weights (W) for each dimension and criterion were calculated using Equations (12) and (13), as presented in Table 7.

Table 7. Normalized weights of sustainable development dimensions and their indicators.

d'	$minV$	W'	W
EC	1.000	1.000	0.428
SC	0.667	0.667	0.286
EN	0.670	0.670	0.287
EC01	0.991	0.991	0.121
EC02	1.000	1.000	0.122
EC03	0.875	0.875	0.107
EC04	0.871	0.871	0.106
EC05	0.950	0.950	0.116
EC06	0.961	0.961	0.118
EC07	0.918	0.918	0.112
EC08	0.855	0.855	0.105
EC09	0.758	0.758	0.093
SC01	1.000	1.000	0.183
SC02	0.910	0.910	0.167
SC03	0.558	0.558	0.102
SC04	0.672	0.672	0.123
SC05	0.712	0.712	0.130
SC06	0.712	0.712	0.130
SC07	0.623	0.623	0.114
SC08	0.273	0.273	0.050
EN01	1.000	1.000	0.207
EN02	0.882	0.882	0.182
EN03	0.817	0.817	0.169
EN04	0.765	0.765	0.158
EN05	0.599	0.599	0.124
EN06	0.420	0.420	0.087
EN07	0.356	0.356	0.074

Next, Equation (14) was applied to sequentially integrate the hierarchical levels, resulting in the overall weight for each criterion, which were then ranked accordingly, as shown in Table 8. Finally, Equation (15) was used to conduct a fuzzy (C.R.) test to validate the effectiveness of the FEAHP questionnaires completed by the 10 respondents. The consistency ratio, computed using the simple arithmetic mean, was 0.069, indicating that the questionnaires were valid.

Table 8. Overall FEAHP weights for sustainable development indicators.

SD Dimension	Dimension Weight	SD Indicator	Indicator Weight	Overall Weight	Rank
EC	0.428	EC01	0.121	0.0518	5
		EC02	0.122	0.0523	3
		EC03	0.107	0.0458	11
		EC04	0.106	0.0455	12
		EC05	0.116	0.0497	7
		EC06	0.118	0.0503	6
		EC07	0.112	0.0480	9
		EC08	0.105	0.0447	14
		EC09	0.093	0.0397	15
SC	0.286	SC01	0.183	0.0523	2
		SC02	0.167	0.0476	10
		SC03	0.102	0.0292	21
		SC04	0.123	0.0351	19
		SC05	0.130	0.0372	16
		SC06	0.130	0.0372	16
		SC07	0.114	0.0326	20
		SC08	0.050	0.0143	24
EN	0.287	EN01	0.207	0.0592	1
		EN02	0.182	0.0522	4
		EN03	0.169	0.0484	8
		EN04	0.158	0.0453	13
		EN05	0.124	0.0355	18
		EN06	0.087	0.0249	22
		EN07	0.074	0.0211	23

Based on the findings of the FEAHP analysis, the indicators ranked by priority are as follows: (EN01) Reducing the emission of harmful substances was ranked first, making it the most critical indicator. (SC01) Reducing the number of health and accident incidents within the enterprise ranked second. (EC02) Reducing procurement costs ranked third. (EN02) Reducing the level of water pollution ranked fourth. Lastly, (EC01) Reducing manufacturing costs ranked fifth.

4.3. Analysis and Results of the First House of Quality

For the prioritisation of key LM methods within the first HoQ, this study adopts the VIKOR method. The integrated correlation matrix (W_{LM}) between SD indicators and LM methods is calculated by multiplying the W_2 and W_3 matrices using Equation (16), resulting in the W_{LM}, as shown in Table 9. Subsequently, the PIS and NIS for the integrated correlation matrix are determined using Equations (18) and (19), with the results presented in Table 10.

Table 9. Integrated correlation matrix of the first house of quality.

	LM1	LM2	LM3	LM4	LM5	LM6	LM7	LM8	LM9	LM10	LM11	LM12	LM13	LM14	LM15	LM16	LM17	LM18	LM19	LM20
EC01	4.63	3.46	5.03	4.75	4.70	5.23	4.39	3.75	5.72	3.27	4.04	3.76	4.65	4.32	5.52	4.01	3.71	2.90	4.23	4.09
EC02	2.59	1.94	2.88	2.64	2.59	2.90	2.53	2.16	3.13	1.83	2.36	2.23	2.61	2.37	3.11	2.10	2.01	1.49	2.20	2.14
EC03	2.28	1.72	2.44	2.18	2.12	2.38	2.11	1.85	2.63	1.63	2.06	1.89	2.13	1.97	2.64	1.63	1.68	1.13	1.72	1.75
EC04	3.02	2.33	3.16	2.86	2.90	3.14	2.73	2.30	3.51	1.86	2.34	2.31	3.10	2.49	3.31	2.35	2.25	1.65	2.40	2.21
EC05	4.14	3.09	4.37	4.22	4.24	4.50	3.82	3.18	5.10	2.74	3.32	3.18	4.40	3.68	4.77	3.67	3.33	2.87	3.84	3.31
EC06	3.38	2.49	3.70	3.66	3.45	3.85	3.32	3.11	4.05	2.58	3.23	3.09	3.29	3.03	4.11	2.62	2.61	1.89	2.85	2.83
EC07	2.44	1.88	2.70	2.51	2.46	2.74	2.43	2.04	3.00	1.76	2.16	2.01	2.45	2.21	2.88	2.00	1.97	1.49	2.06	1.94
EC08	3.01	2.26	3.11	2.87	3.08	3.32	2.81	2.35	3.75	2.00	2.46	2.35	3.07	2.63	3.44	2.60	2.49	1.82	2.60	2.46
EC09	2.23	1.64	2.16	1.89	2.08	2.25	1.96	1.62	2.65	1.38	1.70	1.68	2.23	1.84	2.39	1.82	1.71	1.23	1.83	1.62
SC01	2.87	2.39	2.91	2.81	2.92	3.21	2.66	2.10	3.64	1.78	2.13	1.96	2.87	2.37	3.14	2.54	2.43	1.83	2.54	2.36
SC02	1.20	0.98	1.15	1.00	1.14	1.21	1.09	0.88	1.42	0.71	0.86	0.81	1.08	0.84	1.21	0.78	0.95	0.52	0.88	0.84
SC03	1.20	0.86	1.22	1.16	1.50	1.53	1.43	0.99	1.73	0.92	1.01	0.93	1.24	1.13	1.44	0.99	1.43	0.70	0.96	1.04
SC04	3.33	2.74	3.58	3.32	3.27	3.53	2.99	2.71	4.01	2.13	2.69	2.67	3.34	2.65	3.75	2.60	2.46	1.83	2.92	2.70
SC05	2.25	1.76	2.43	2.12	2.43	2.56	2.20	1.81	2.97	1.56	1.95	1.83	2.26	1.90	2.65	1.82	2.00	1.26	2.04	2.01
SC06	1.57	1.19	1.59	1.55	1.71	1.85	1.62	1.27	2.04	1.08	1.30	1.19	1.60	1.35	1.83	1.30	1.48	0.95	1.29	1.28
SC07	2.24	1.74	2.30	2.12	2.13	2.32	1.93	1.67	2.64	1.39	1.74	1.70	2.33	1.77	2.45	1.76	1.61	1.29	1.91	1.63
SC08	1.22	0.94	1.30	1.32	1.34	1.40	1.18	1.06	1.51	0.87	1.03	1.05	1.31	1.07	1.42	1.12	0.99	0.82	1.14	0.99
EN01	2.13	1.76	2.23	2.11	2.26	2.32	2.06	1.72	2.62	1.32	1.66	1.60	2.15	1.72	2.41	1.77	1.71	1.31	1.90	1.65
EN02	2.07	1.74	2.17	2.06	2.18	2.22	1.95	1.68	2.52	1.27	1.59	1.55	2.08	1.64	2.30	1.73	1.59	1.27	1.87	1.60
EN03	2.06	1.72	2.16	2.03	2.16	2.23	1.96	1.67	2.52	1.27	1.61	1.56	2.08	1.64	2.31	1.71	1.60	1.23	1.83	1.59
EN04	2.00	1.68	2.09	1.96	2.10	2.14	1.87	1.62	2.43	1.23	1.54	1.50	2.01	1.56	2.22	1.66	1.54	1.20	1.78	1.53
EN05	1.88	1.53	1.97	1.89	2.01	2.08	1.83	1.56	2.31	1.17	1.47	1.43	1.92	1.52	2.12	1.58	1.48	1.15	1.68	1.45
EN06	2.47	1.77	2.50	2.28	2.52	2.58	2.25	1.91	3.01	1.72	2.09	2.05	2.56	2.13	2.85	2.02	2.04	1.43	2.04	1.87
EN07	1.68	1.35	1.77	1.72	1.84	1.95	1.71	1.41	2.11	1.10	1.41	1.34	1.73	1.42	1.98	1.38	1.39	0.96	1.45	1.35

Table 10. Lean management methods: positive and negative ideal solutions.

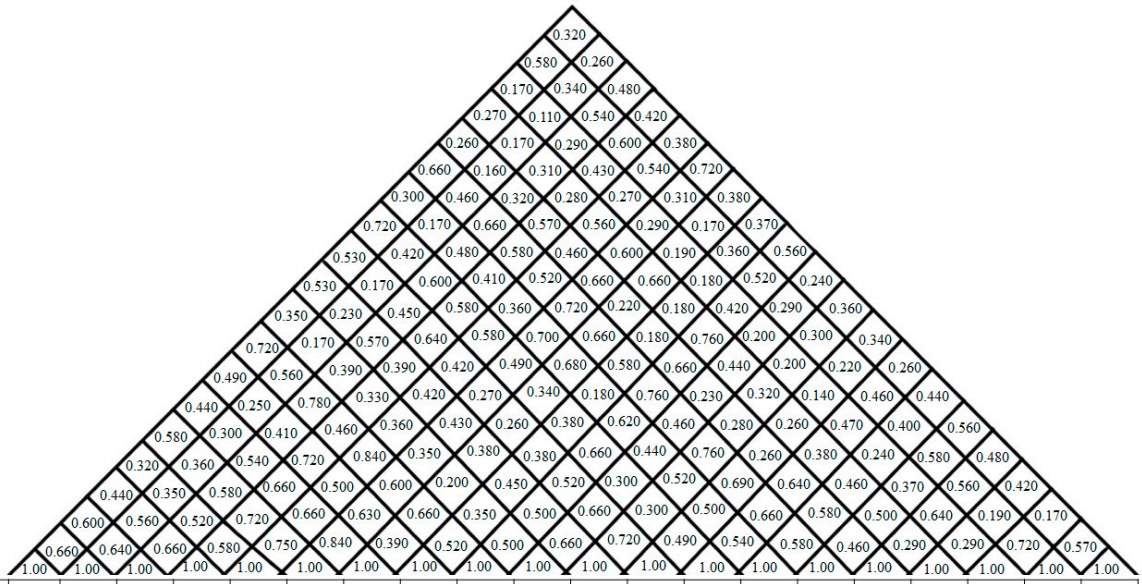
	PIS	NIS
LM01	4.625	1.195
LM02	3.458	0.856
LM03	5.029	1.153
LM04	4.753	1.003
LM05	4.697	1.143
LM06	5.234	1.211
LM07	4.388	1.094
LM08	3.755	0.881
LM09	5.724	1.419
LM10	3.274	0.707
LM11	4.037	0.859
LM12	3.763	0.808
LM13	4.655	1.082
LM14	4.324	0.840
LM15	5.517	1.212
LM16	4.006	0.784
LM17	3.709	0.953
LM18	2.898	0.519
LM19	4.229	0.883
LM20	4.093	0.841

The resulting integrated correlation matrix (WLM) is then normalised using Equation (20). A weighted normalised matrix is in which the normalised values are multiplied by their corresponding weights, as derived from the FEAHP calculations. Finally, Equations (21) and (22) are employed to calculate the group utility value S_j and the individual regret value R_j. Subsequently, Equation (23) is used—setting the decision-making coefficient V to 0.5—to derive the aggregated index values Q_j for each alternative. The results are presented in Table 11.

Table 11. Aggregated index values Q_j of lean management methods.

LM Methods	S_j	R_j	Q_j	Rank
LM01	1.336	0.079	0.912	19
LM02	1.312	0.078	0.825	16
LM03	1.286	0.076	0.635	11
LM04	1.256	0.074	0.411	6
LM05	1.309	0.078	0.803	15
LM06	1.290	0.076	0.664	12
LM07	1.319	0.078	0.876	17
LM08	1.291	0.077	0.673	14
LM09	1.320	0.078	0.879	18
LM10	1.258	0.075	0.435	8
LM11	1.257	0.075	0.420	7
LM12	1.259	0.075	0.436	9
LM13	1.291	0.077	0.666	13
LM14	1.229	0.073	0.213	2
LM15	1.271	0.075	0.524	10
LM16	1.230	0.073	0.219	3
LM17	1.330	0.079	0.960	20
LM18	1.200	0.071	0.000	1
LM19	1.251	0.074	0.372	5
LM20	1.245	0.074	0.335	4

According to the results of the VIKOR analysis, (LM18) Andon was ranked first, indicating it is the most important LM method. Following that, (LM14) U-shaped production line ranked second, (LM16) Poka-yoke (error-proofing device) ranked third, (LM20) Elimination of non-load operations ranked fourth, and (LM19) Identification of equipment failure points and root causes ranked fifth. All the above results have been summarized in the HoQ, as illustrated in Figure 7.



	Weight	LM01	LM02	LM03	LM04	LM05	LM06	LM07	LM08	LM09	LM10	LM11	LM12	LM13	LM14	LM15	LM16	LM17	LM18	LM19	LM20
EC01	0.0518	0.530	0.310	0.700	0.290	0.430	0.550	0.410	0.280	0.720	0.260	0.320	0.130	0.540	0.420	0.720	0.390	0.280	0.110	0.630	0.530
EC02	0.0523	0.310	0.020	0.570	0.290	0.250	0.310	0.270	0.090	0.420	0.140	0.280	0.040	0.370	0.130	0.570	0.120	0.040	0.030	0.120	0.180
EC03	0.0458	0.290	0.200	0.490	0.090	0.090	0.390	0.160	0.190	0.420	0.150	0.230	0.150	0.190	0.170	0.440	0.010	0.060	0.040	0.060	0.040
EC04	0.0455	0.570	0.180	0.530	0.310	0.340	0.390	0.160	0.060	0.510	0.010	0.180	0.020	0.720	0.130	0.360	0.090	0.210	0.030	0.100	0.100
EC05	0.0497	0.630	0.230	0.590	0.350	0.510	0.450	0.310	0.110	0.550	0.090	0.190	0.070	0.760	0.220	0.540	0.420	0.510	0.250	0.670	0.080
EC06	0.0503	0.370	0.150	0.500	0.460	0.390	0.420	0.360	0.460	0.420	0.250	0.450	0.290	0.310	0.190	0.540	0.030	0.090	0.130	0.160	0.290
EC07	0.0480	0.340	0.130	0.530	0.250	0.190	0.390	0.240	0.160	0.490	0.160	0.180	0.070	0.200	0.160	0.360	0.120	0.130	0.210	0.060	0.030
EC08	0.0447	0.570	0.210	0.230	0.150	0.450	0.330	0.220	0.100	0.750	0.090	0.180	0.040	0.400	0.150	0.390	0.300	0.210	0.140	0.160	0.260
EC09	0.0397	0.670	0.080	0.080	0.130	0.250	0.180	0.070	0.040	0.750	0.010	0.050	0.020	0.220	0.220	0.310	0.210	0.100	0.050	0.090	0.050
SC01	0.0523	0.690	0.590	0.160	0.200	0.400	0.420	0.130	0.030	0.610	0.010	0.050	0.020	0.050	0.040	0.190	0.580	0.530	0.150	0.250	0.140
SC02	0.0476	0.410	0.190	0.070	0.050	0.240	0.150	0.070	0.040	0.340	0.010	0.010	0.010	0.010	0.010	0.070	0.010	0.160	0.010	0.010	0.040
SC03	0.0292	0.270	0.020	0.020	0.020	0.360	0.210	0.150	0.060	0.280	0.030	0.030	0.030	0.090	0.030	0.060	0.030	0.550	0.010	0.060	0.030
SC04	0.0351	0.560	0.400	0.510	0.440	0.510	0.150	0.110	0.210	0.630	0.040	0.120	0.100	0.450	0.100	0.510	0.120	0.180	0.040	0.190	0.430
SC05	0.0372	0.460	0.120	0.310	0.060	0.600	0.150	0.060	0.040	0.520	0.030	0.100	0.040	0.130	0.030	0.460	0.090	0.310	0.030	0.140	0.370
SC06	0.0372	0.340	0.150	0.090	0.060	0.310	0.280	0.120	0.100	0.250	0.010	0.090	0.040	0.130	0.010	0.210	0.140	0.400	0.090	0.060	0.030
SC07	0.0326	0.500	0.180	0.390	0.120	0.390	0.240	0.090	0.030	0.220	0.090	0.030	0.030	0.460	0.030	0.400	0.160	0.120	0.090	0.120	0.090
SC08	0.0143	0.200	0.060	0.030	0.250	0.270	0.120	0.100	0.040	0.240	0.090	0.090	0.030	0.210	0.030	0.120	0.090	0.030	0.090	0.090	0.090
EN01	0.0592	0.380	0.280	0.130	0.250	0.490	0.290	0.130	0.010	0.550	0.010	0.010	0.010	0.120	0.030	0.450	0.110	0.090	0.120	0.190	0.010
EN02	0.0522	0.380	0.290	0.130	0.280	0.490	0.290	0.070	0.010	0.550	0.010	0.010	0.010	0.120	0.030	0.390	0.100	0.030	0.120	0.190	0.030
EN03	0.0484	0.380	0.280	0.130	0.260	0.490	0.290	0.070	0.010	0.550	0.010	0.010	0.010	0.120	0.030	0.450	0.100	0.030	0.120	0.130	0.030
EN04	0.0453	0.380	0.280	0.130	0.250	0.490	0.290	0.040	0.010	0.550	0.010	0.010	0.010	0.120	0.010	0.390	0.100	0.030	0.120	0.130	0.030
EN05	0.0355	0.380	0.190	0.130	0.230	0.490	0.290	0.100	0.030	0.460	0.010	0.010	0.010	0.120	0.030	0.360	0.100	0.030	0.120	0.130	0.010
EN06	0.0249	0.380	0.100	0.130	0.110	0.430	0.220	0.130	0.040	0.550	0.120	0.210	0.090	0.540	0.090	0.500	0.100	0.210	0.040	0.150	0.100
EN07	0.0211	0.260	0.200	0.110	0.130	0.490	0.280	0.130	0.040	0.250	0.030	0.030	0.040	0.160	0.030	0.460	0.090	0.090	0.030	0.090	0.030
Q_j		0.912	0.825	0.635	0.411	0.803	0.664	0.876	0.673	0.879	0.435	0.420	0.436	0.666	0.213	0.524	0.219	0.960	0.000	0.372	0.335
RANK		19	16	11	6	15	12	17	14	18	8	7	9	13	**2**	10	**3**	20	**1**	**5**	**4**

Figure 7. Organisational structure model of the first house of quality.

The Andon system is vital in automotive manufacturing as it enables real-time problem identification and alerts operators immediately. This rapid detection minimizes downtime and supports continuous improvement by empowering workers to stop the production line to address issues quickly. Its role in maintaining product quality and operational efficiency explains its top ranking in this study.

4.4. Analysis and Results of the Second House of Quality

Following the methodology and computational procedures previously described for the first HoQ, the integrated correlation matrix for the second HoQ (denoted as W_{DT}) was derived by multiplying matrices W_5 and W_6 using Equation (17), as presented in Table 12.

Table 12. Integrated correlation matrix of the second house of quality.

	DT01	DT02	DT03	DT04	DT05	DT06	DT07	DT08	DT09	DT10	DT11	DT12	DT13	DT14	DT15	DT16	DT17
LM01	2.400	2.718	1.999	2.202	2.233	2.065	2.085	2.743	2.563	2.124	1.995	2.833	1.982	2.299	2.555	3.029	2.453
LM02	0.784	0.770	0.815	0.637	0.715	0.659	0.602	0.852	0.834	0.663	0.634	0.858	0.693	0.631	0.786	0.982	0.758
LM03	1.174	1.244	1.001	0.976	0.972	1.005	1.004	1.290	1.253	0.965	0.879	1.302	0.856	1.071	1.237	1.420	1.098
LM04	2.202	2.257	1.841	1.685	1.744	2.081	2.039	2.374	2.255	1.637	1.483	2.349	1.584	2.025	2.211	2.606	2.073
LM05	2.235	2.413	1.748	1.745	1.985	1.878	1.875	2.561	2.362	2.059	1.944	2.566	1.622	2.056	2.310	2.687	2.241
LM06	1.741	2.007	1.561	1.831	2.156	1.583	1.582	2.207	2.355	2.067	2.072	2.277	1.186	1.716	2.075	2.487	2.162
LM07	0.702	0.882	0.642	0.736	1.035	0.624	0.666	1.025	1.029	1.212	1.233	1.132	0.456	0.794	0.974	1.139	1.087
LM08	1.273	1.410	1.017	1.060	1.300	1.312	1.296	1.601	1.592	1.578	1.474	1.721	0.908	1.407	1.590	1.835	1.692
LM09	2.896	3.301	2.576	2.763	3.097	2.905	2.901	3.592	3.530	3.201	3.071	3.789	2.261	3.109	3.465	4.151	3.620
LM10	0.743	0.771	0.673	0.616	0.770	0.710	0.783	0.859	0.897	0.760	0.735	0.924	0.461	0.724	0.805	0.992	0.865
LM11	0.757	0.744	0.631	0.565	0.715	0.721	0.829	0.838	0.878	0.776	0.725	0.940	0.440	0.752	0.805	0.988	0.873
LM12	0.730	0.788	0.596	0.554	0.734	0.580	0.620	0.871	0.852	0.950	0.890	0.992	0.492	0.695	0.848	0.949	0.850
LM13	2.790	2.940	2.319	2.134	2.467	2.310	2.266	3.129	3.029	2.677	2.518	3.197	2.119	2.492	2.948	3.411	2.880
LM14	0.676	0.666	0.529	0.484	0.609	0.676	0.630	0.763	0.772	0.609	0.566	0.764	0.385	0.619	0.697	0.840	0.723
LM15	1.933	2.077	1.683	1.495	1.763	1.741	1.717	2.213	2.175	1.991	1.913	2.344	1.497	1.894	2.101	2.518	2.176
LM16	0.837	1.066	0.754	0.846	1.259	0.709	0.752	1.202	1.245	1.521	1.513	1.300	0.479	0.903	1.171	1.341	1.321
LM17	0.560	0.613	0.483	0.434	0.638	0.473	0.468	0.722	0.735	0.740	0.753	0.733	0.322	0.530	0.667	0.761	0.710
LM18	1.317	1.467	0.909	0.966	1.238	1.113	1.165	1.571	1.413	1.355	1.312	1.543	0.838	1.244	1.350	1.571	1.477
LM19	1.047	1.259	0.868	1.006	1.347	1.108	1.057	1.462	1.417	1.487	1.379	1.491	0.836	1.126	1.331	1.640	1.555
LM20	0.831	0.899	0.643	0.714	0.798	0.883	0.871	0.992	1.014	0.854	0.801	1.074	0.578	0.912	0.975	1.147	1.029

Subsequently, the PIS and NIS for the W_{DT} matrix were determined using Equations (18) and (19), with the results shown in Table 13. Thereafter, the W_{DT} matrix was normalised using Equation (20). The weighted normalised matrix was then constructed, where the values in the normalised matrix were multiplied by their respective weights. These weights were derived from the Q_j values obtained from the first HoQ's W_{LM} matrix. Specifically, the Q_j values were transformed using $(1 - Q_j)$ and used as decision weights in the second HoQ [122,123]. The final weighted matrix was obtained by multiplying the normalized matrix by the corresponding weights $(1 - Q_j)$. Subsequently, Equations (21) and (22) were applied to compute the group utility values S_j and the individual regret values R_j. Using Equation (23), and setting the decision-making coefficient V to 0.5, the aggregated index values Q_j were derived. The results are presented in Table 14.

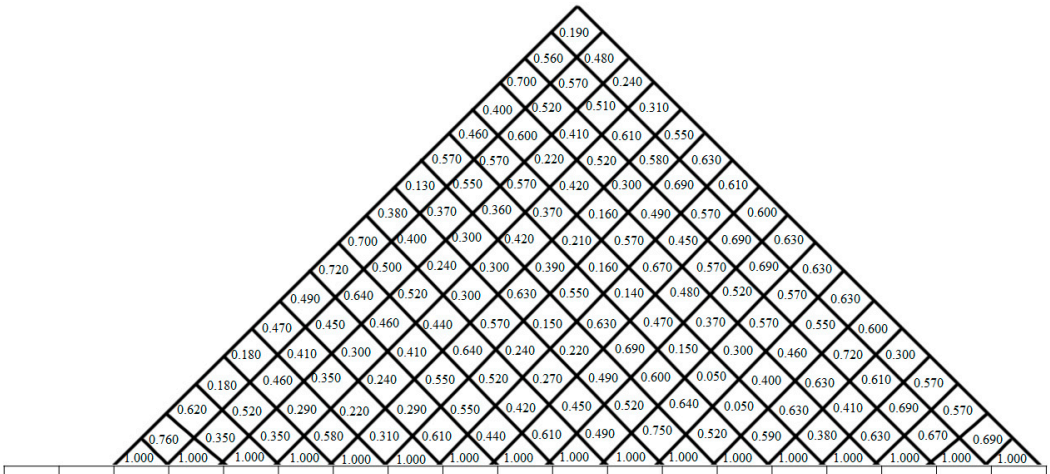
Table 13. Positive and negative ideal solutions of digital transformation technologies.

	PIS	NIS
DT01	2.896	0.560
DT02	3.301	0.613
DT03	2.576	0.483
DT04	2.763	0.434
DT05	3.097	0.609
DT06	2.905	0.473
DT07	2.901	0.468
DT08	3.592	0.722
DT09	3.530	0.735
DT10	3.201	0.609
DT11	3.071	0.566
DT12	3.789	0.733
DT13	2.261	0.322
DT14	3.109	0.530
DT15	3.465	0.667
DT16	4.151	0.761
DT17	3.620	0.710

Table 14. Aggregated index values Q_j of Digital transformation technologies.

DT Technologies	S_j	R_j	Q_j	Rank
DT01	1.221	0.139	0.734	11
DT02	1.211	0.138	0.643	7
DT03	1.210	0.139	0.647	8
DT04	1.167	0.134	0.229	2
DT05	1.227	0.140	0.802	14
DT06	1.176	0.135	0.307	4
DT07	1.174	0.134	0.282	3
DT08	1.236	0.141	0.886	16
DT09	1.247	0.143	1.000	17
DT10	1.217	0.139	0.708	10
DT11	1.208	0.138	0.612	6
DT12	1.225	0.140	0.786	13
DT13	1.144	0.131	0.000	1
DT14	1.188	0.136	0.423	5
DT15	1.222	0.140	0.759	12
DT16	1.211	0.139	0.651	9
DT17	1.228	0.140	0.814	15

According to the results obtained from the VIKOR method, (DT13) Customer Relationship Management ranked first, making it the most critical DT technology. This was followed by (DT04) Computer-Aided Design in second place, and (DT07) Energy Management System in third. (DT06) Carbon Management System Platform ranked fourth, while (DT14) Smart Grid came in fifth. The overall results from the second HoQ are summarised in Figure 8.



	Weight	DT01	DT02	DT03	DT04	DT05	DT06	DT07	DT08	DT09	DT10	DT11	DT12	DT13	DT14	DT15	DT16	DT17
LM01	0.010	0.250	0.540	0.250	0.510	0.330	0.220	0.270	0.230	0.280	0.270	0.210	0.420	0.400	0.150	0.150	0.150	0.180
LM02	0.020	0.060	0.040	0.310	0.030	0.180	0.100	0.040	0.030	0.100	0.130	0.040	0.060	0.210	0.030	0.060	0.100	0.050
LM03	0.042	0.330	0.090	0.130	0.310	0.060	0.150	0.150	0.100	0.160	0.120	0.150	0.100	0.150	0.090	0.030	0.060	0.100
LM04	0.067	0.460	0.270	0.370	0.300	0.310	0.450	0.420	0.200	0.150	0.080	0.080	0.180	0.180	0.180	0.140	0.180	0.180
LM05	0.023	0.370	0.390	0.190	0.170	0.330	0.180	0.160	0.400	0.240	0.360	0.300	0.340	0.230	0.280	0.100	0.110	0.120
LM06	0.038	0.160	0.160	0.130	0.460	0.400	0.130	0.160	0.130	0.550	0.300	0.550	0.290	0.110	0.050	0.140	0.110	0.130
LM07	0.014	0.030	0.060	0.030	0.090	0.120	0.030	0.030	0.090	0.100	0.360	0.540	0.210	0.040	0.030	0.030	0.040	0.030
LM08	0.037	0.210	0.090	0.040	0.060	0.030	0.090	0.090	0.090	0.120	0.330	0.300	0.240	0.010	0.090	0.120	0.390	0.390
LM09	0.014	0.260	0.300	0.390	0.510	0.390	0.350	0.410	0.210	0.300	0.570	0.540	0.420	0.270	0.230	0.210	0.510	0.540
LM10	0.065	0.100	0.010	0.120	0.090	0.130	0.090	0.300	0.030	0.150	0.140	0.190	0.070	0.070	0.010	0.010	0.070	0.030
LM11	0.066	0.090	0.010	0.090	0.030	0.060	0.030	0.360	0.030	0.150	0.180	0.150	0.090	0.030	0.010	0.010	0.180	0.030
LM12	0.065	0.120	0.090	0.070	0.010	0.040	0.030	0.030	0.030	0.070	0.300	0.300	0.270	0.060	0.030	0.030	0.030	0.030
LM13	0.038	0.460	0.480	0.360	0.120	0.230	0.120	0.120	0.230	0.400	0.450	0.450	0.390	0.360	0.100	0.230	0.400	0.400
LM14	0.090	0.120	0.030	0.030	0.030	0.090	0.180	0.120	0.090	0.150	0.090	0.100	0.040	0.030	0.030	0.040	0.090	0.030
LM15	0.054	0.230	0.360	0.360	0.030	0.060	0.150	0.120	0.060	0.240	0.390	0.420	0.300	0.210	0.150	0.030	0.420	0.330
LM16	0.089	0.090	0.120	0.030	0.090	0.120	0.010	0.010	0.070	0.130	0.560	0.640	0.100	0.030	0.010	0.030	0.060	0.120
LM17	0.005	0.120	0.030	0.030	0.010	0.040	0.040	0.010	0.090	0.130	0.150	0.340	0.070	0.030	0.010	0.030	0.030	0.070
LM18	0.114	0.090	0.450	0.010	0.010	0.040	0.030	0.210	0.390	0.140	0.270	0.300	0.150	0.010	0.010	0.040	0.140	0.170
LM19	0.072	0.090	0.120	0.030	0.030	0.240	0.010	0.010	0.190	0.050	0.430	0.120	0.150	0.040	0.010	0.030	0.410	0.420
LM20	0.076	0.090	0.060	0.010	0.090	0.070	0.120	0.120	0.040	0.190	0.090	0.090	0.180	0.030	0.100	0.090	0.150	0.180
1-Q_j		0.737	0.661	0.627	0.245	0.810	0.352	0.333	0.898	1.000	0.744	0.657	0.807	0.000	0.461	0.774	0.687	0.841
RANK		10	8	6	**2**	14	**4**	**3**	16	17	11	7	13	**1**	**5**	12	9	15

Figure 8. Organisational structure model of the second house of quality.

4.5. Results and Discussion

This research focused on Taiwan's automotive industry as the subject for research and empirical analysis. Drawing on the results of the two HoQ analyses, the interrelationships among SD indicators, LM methods, and DT technologies were identified. Furthermore, key LM methods and DT technologies that positively and critically impact the enhancement of corporate SD performance were determined. The following implications are proposed for managers in Taiwan's automotive industry based on the findings:

The results indicate that companies pursuing SD goals should pay particular attention to the following areas: reducing the emission of hazardous substances, lowering internal health and accident rates, decreasing procurement costs, mitigating the degree of water pollution, and reducing manufacturing costs. These SD indicators are closely aligned with the core concepts of factory SQCD management (Safety, Quality, Cost, Delivery).

1. Safety measures—including Andon systems, error-proofing devices, and the elimination of non-value-added operations—play a crucial role in reducing the incidence of accidents and improving overall factory safety. Coupled with CAD, it is possible to

design safer work environments and operating processes from the source, further improving overall factory safety. CAD technologies can precisely simulate and analyze various operational scenarios, helping engineers and designers identify and resolve potential safety risks at the design stage, thereby effectively preventing accidents and safeguarding employee health and safety.

2. Quality improvement can be achieved by applying LM methods such as U-shaped production lines combined with error-proofing devices, and by identifying the true causes and locations of equipment failures. Reducing errors and defects during the manufacturing process effectively minimizes waste generation, thus reducing emissions of hazardous substances. Through precise design and efficient production management, factories can achieve more environmentally friendly manufacturing processes, contributing to the SD indicator target of reducing water pollution. Furthermore, integrating CRM systems can enhance product quality control and customer satisfaction.
3. Cost management can be significantly enhanced through the adoption of DT technologies, such as Energy Management Systems and Carbon Management System Platforms, which help reduce energy and resource expenses. When integrated with Smart Grid technology, energy consumption can be efficiently controlled at the source, leading to improved energy efficiency and a reduction in unnecessary usage. This not only lowers energy costs but also decreases carbon emissions. Additionally, minimizing wastewater generation helps mitigate the risk of water pollution. In automotive manufacturing, for instance, significant amounts of water are used during sheet metal welding to cool joints and during vehicle surface treatment for cleaning, rinsing, and equipment maintenance. These examples highlight the importance of implementing effective water resource management and pollution control measures in the automotive industry to reduce water pollution and enhance water use efficiency.
4. On-time delivery can be achieved by utilizing LM methods such as U-shaped production lines, which enhance production flexibility and responsiveness to market changes. Faster delivery times reduce inventory requirements, lower inventory costs, and consequently reduce procurement costs. Furthermore, CRM systems, built upon the foundations of high product quality and short lead times, ensure product quality, ultimately boosting customer satisfaction and business efficiency.

Therefore, the integrated use of LM and DT technologies to explore and implement applications toward SD objectives will help enterprises pursue SD while simultaneously enhancing competitiveness. This integrated approach not only helps companies tackle present SD challenges but also establishes a strong foundation for long-term sustainable operations.

4.6. Comparison with Previous Studies

Previous literature has mostly focused on exploring the relationships between LM and SD (e.g., [15,22,23,65,66]), DT and SD (e.g., [16,17]), or LM and DT individually (e.g., [14,15]). However, there has been a lack of in-depth discussion on the combined effects of these three elements, and no integrated conceptual framework has been proposed. Moreover, existing studies have been insufficient in quantitatively analyzing the impact of SD, LM, and DT on corporate performance, often lacking concrete data support. This study aims to provide more specific and comprehensive insights through systematic thinking and in-depth analysis. It also seeks to expand the scope of related research, thereby promoting further academic exploration on this topic.

Regarding LM methods, no prior research has attempted to classify them hierarchically. Studies on JIT and Jidoka have mostly treated these as individual improvement methods

without analyzing their relationships with other methods [69–73]. However, this study argues that JIT and Jidoka represent improvement stages or goals rather than methods that should be discussed on the same level as others. Therefore, a hierarchical structure needs to be established for them. This represents a significant contribution of the current study.

In addition, our findings regarding the role of LM in improving operational efficiency are consistent with earlier studies that emphasized waste reduction and process optimization as the core benefits of LM [65–68]. Likewise, our findings regarding DT as a catalyst for achieving sustainability goals are consistent with previous research that underscores the potential of digital technologies—such as IoT, Big Data, and AI—to advance sustainable practices [86–88]. By integrating LM, DT, and SD into a unified framework and applying it to Taiwan's automotive industry, this study contributes new insights that extend the scope of prior research.

5. Conclusions

The growth of the automotive industry is a vital driving force behind the economic development of emerging countries. However, many studies have emphasized that economic growth must not neglect the importance of SD. SD is no longer simply a moral or environmental concern: it has evolved into a critical source of competitive advantage for modern enterprises. Developing an industry that balances environmental protection, social equity, and economic efficiency—while preventing the widening of disparities and fostering an environment conducive to sustainable industrial growth—poses a significant challenge that must be addressed. Numerous scholars have emphasized that integrating LM and DT can create a synergistic effect, enhancing industrial competitiveness, improving environmental performance, reducing costs, and minimizing environmental impact. Consequently, a deeper investigation into the interrelationships among LM, DT, and SD is essential to establish the most effective integrated approach for achieving sustainable corporate development.

5.1. Managerial Implications

Regarding the discussion on improving SD performance through LM and DT, most existing studies have focused only on the relationships between LM and SD, DT and SD, or LM and DT. To date, the literature has lacked an integrated analysis that examines the combined effects of all three elements and proposes a complete conceptual framework. As a result, the reference value for developing integrated approaches has been limited, and there remains a lack of comprehensive quantitative analysis regarding their performance impacts. This study adopts a systems thinking approach by utilizing two HoQ frameworks to analyze SD, LM, and DT, investigating the interrelationships among them and identifying which LM methods and DT technologies serve as critical strategies that positively influence corporate SD performance. It is anticipated that the findings of this study will contribute to advancing the frontiers of related research. Furthermore, the methodological framework presented in this study is adaptable to various industries and enterprises, highlighting the original contribution and significance of this research.

5.2. Limitations and Directions for Future Research

This study acknowledges several specific limitations. A two-stage evaluation framework was developed to investigate the interactions and interrelationships among SD, LM, and DT. Nonetheless, there remain areas for improvement, including the following:

1. Due to time and budget constraints, the sample size for the HoQ questionnaires was relatively limited. The survey was administered exclusively to core manufacturers and first-tier component suppliers within the automotive industry.

2. In assessing the importance of SD indicators, this study considered only fuzzy uncertainty and did not account for the interrelationships among the indicators.

For future research directions, the following suggestions are proposed:

1. The framework developed in this study could be expanded to incorporate second-tier component suppliers, allowing for a more comprehensive and detailed analysis.
2. Since the importance evaluation of SD indicators in this study only addressed fuzzy uncertainty, future researchers are encouraged to adopt the fuzzy ANP to capture the interdependencies among indicators and thereby produce results that are more applicable to real-world scenarios.
3. The findings indicate that experts in the automotive industry place relatively high importance on the economic dimension of SD. Therefore, future studies could focus on identifying specific methods and indicators within the economic dimension that enterprises should adopt to improve their economic sustainability performance.

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Abbreviations

The following abbreviations are used throughout this manuscript:

SD	Sustainable Development
LM	Lean Management
DT	Digital Transformation
HoQ	House of Quality
MADM	Multiple Attribute Decision Making
QFD	Quality function deployment
FEAHP	Fuzzy Extended Analytic Hierarchy Process
FDM	Fuzzy Delphi method
VIKOR	VlseKriterijumska Optimizacija I Kompromisna Resenje

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