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Evaluating the Interrelationships of Industrial 5.0 Development Factors Using an Integration Approach of Fermatean Fuzzy Logic

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ABSTRACT

The maturation of the Industry 4.0 concept has brought numerous benefits to human society; however, it is not without challenges, including neglect of worker welfare, vulnerability of global supply chains, and environmental degradation. To enhance the adaptability of the Industry 4.0 concept, Industry 5.0 has been developed, though its practical implementation has not yet been fully realized. This paper presents a novel conceptual framework to analyze and evaluate the complex interrelationships of development factors in Industry 5.0. Through extensive literature review and prolonged interviews with experts, three critical dimensions and their 18 key factors for the development of Industry 5.0 have been identified. A combination of Fermatean Fuzzy Sets (FFs) and Decision-Making Trial and Evaluation Laboratory (DEMATEL) has been employed to discern the interrelationships among these factors, and an Influential Network Relationship Map (INRM) has been constructed to aid decision-makers in formulating improvement strategies. The results indicate that "Sustainable Development" is the most influential dimension, with the factors "Renewable Energy," "Data-Driven Analysis Technologies," and "Distributed Control" emerging as the most significant within their respective dimensions.

1. Introduction

To address the limitations of Industry 4.0, the European Union introduced the concept of Industry 5.0 in 2021, focusing on the development and enhancement of three key aspects: human-centricity, process flexibility, and sustainable development [1]. Industry 5.0 emphasizes a value-driven approach, that recenters the human in the operational system to ensure a high degree of personalization and collaboration [2]. It also incorporates humanistic considerations into production processes, prioritizing the safety and well-being of workers and enhancing the interaction between humans, machines, processes, and systems [3]. The COVID-19 pandemic has had a profound impact

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on global supply chains, compelling businesses to reassess and modify traditional supply chain strategies to adapt to changing perspectives and environments. The process flexibility emphasized in Industry 5.0 is not about introducing a new model but about embedding flexibility into existing operational systems or production processes [4].

Since the Industrial Revolution, human activities have accelerated greenhouse gas emissions, and the convenience of modern life has come at the cost of environmental depletion and sacrifice. However, ecological resources are not inexhaustible. In 2015, the United Nations announced the "2030 Sustainable Development Goals (SDGs)," to guide global efforts toward sustainability. Kasinathan*, et al.* [5] noted that future societies should strive towards these sustainable development goals, with Industry 5.0 playing a crucial role in this endeavor. Recent research by various researchers highlights the importance of the global supply chain in Industry 5.0 era [6]. Nevertheless, studies that discuss the interplay of multiple factors of Industrial 5.0 development are needed.

Decision-Making Trial and Evaluation Laboratory (DEMATEL) is a technique utilized for assessing the reciprocal impact among various factors. It involves expert-driven pairwise comparisons to ascertain both indirect and direct influences among these factors. The cumulative impacts are then computed to establish of the influence relationship of the system. DEMATEL's application is extensive across numerous decision-making scenarios [7]. Moreover, Fermatean Fuzzy sets (FFs) enhance the capabilities of Pythagorean fuzzy sets (PFs) in capturing uncertainty. FFs provide a broader spectrum for addressing information uncertainty, mitigating the risk of losing vital information during semantic conversions [8]. In this context, FFs are amalgamated with DEMATEL, offering a nuanced approach to incorporate expert uncertainty in evaluations [9].

Therefore, in this study, the Fermatean fuzzy decision-making trial and evaluation laboratory (FF-DEMATEL) method is used to identify the interrelationships among key factors that are critical to the successful development of Industry 5.0. On the other hand, the FF-DEMATEL can be employed to generate an Influential Network Relationship Map (INRM). This way allows for the visualization of the analysis results, offering decision-makers a clear and structured view of the influence among all factors involved. This visual representation enhances understanding and aids in the decision-making process by delineating the intricate relationships and impact levels of various factors. Overall, this paper offers a contribution to the field of industrial development, particularly in the context of the evolving landscape of Industry 5.0. It provides practical tools and analytical insights that can guide strategic decision-making and foster the sustainable growth of industries in alignment with Industry 5.0 ideals. The main strengths and benefits of this paper are delineated as follows:

i. An assessment framework for the development of Industry 5.0 has been established for enterprises and decision-makers to use as a basis for examination. Such a framework is essential because it allows them to examine the extent to which their progress and operations are in line with the premises of Industry 5.0.
ii. The FF-DEMATEL approach helps to collect various information that might have been overlooked. It helps to establish connections between different evaluated factors, determine their relative weights, and rank them in terms of influence. Such an approach makes the analysis more precise and ensures a comprehensive understanding of the dynamic among the assessed factors.
iii. Enterprises and policymakers can utilize insights from the INRM and interrelationships of assessment factors to formulate policies and initiatives that drive toward the realization of Industry 5.0.

iv. The assessment framework provided here is replicable and scalable. These characteristics make it flexible enough to be adapted in different industrial contexts, thus enhancing its widespread use and possible further improvement across diverse settings.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on Industry 4.0 and Industry 5.0. Section 3 introduces the FF-DEMATEL technique. Data analysis and results are presented in Section 4. Implications and conclusions are discussed in Sections 5 and 6, respectively.

2. Literature Review

The evolution from Industry 4.0 to Industry 5.0 signifies a substantial shift in the industrial paradigm. It involves the implementation of advanced technological innovations with a renewed emphasis on human-centricity, sustainability, and resilience. The most commonly utilized aspects of Industry 4.0 were IoT and artificial intelligence technologies to improve manufacturing processes, which were mainly characterized by digitization and automation [10]. However, this tech-centric approach overlooked crucial factors such as worker welfare and environmental sustainability. As a response, Industry 5.0 emerged with the goal of integrating technological advancements with human-centric values and sustainable practices [11].

Singh*, et al.* [12] discussed the challenges of integrating IoT into industrial infrastructures for Industry 4.0. They proposed the "Fusion Fed Block" solution as a potential solution. Innovative thinking like this leads to more extensive and robust approaches, as seen in Industry 5.0. Also, Li*, et al.* [13] and Melendez*, et al.* [14] emphasized the importance of safety and collaborative efficiency in the workplace. They proposed methods to ensure worker safety, especially in human-machine interaction. A significant shift in Industry 5.0 is the prioritization of sustainable development. Kasinathan, Pugazhendhi, Elavarasan, Ramachandaramurthy, Ramanathan, Subramanian, Kumar, Nandhagopal, Raghavan and Rangasamy [5] emphasized the impact of investigation into the potential for collaboration between industry 4.0 innovations and renewable energy initiatives with a particular emphasis on environmental management within corporate strategies.

Methodologically, recent studies have introduced new frameworks to deal with the complexities of Industry 5.0. For instance, Sindhwani*, et al.* [15] proposed a new multi-criteria analysis framework, while Leng*, et al.* [16] developed the Blockchained Smart Contract Pyramid-Driven Multi-Agent Autonomous Process Control (BSCP-MAAPC) approach, respectively. This study differs from previous ones that relied on more static models or concepts that did not account for future changes in the digital space, such as big data or artificial intelligence.

The transition from Industry 4.0 to Industry 5.0 has significant strategic implications, especially in manufacturing, supply chain management, and environmental policy (Karmaker*, et al.* [17]; Ghobakhloo*, et al.* [18]; Pinciroli*, et al.* [19]; Tran*, et al.* [20]; Ojstersek*, et al.* [21]; Orso*, et al.* [22]; Fraga-Lamas*, et al.* [23]). Numerous studies, whether based on Industry 4.0 or developing the foundations of Industry 5.0, have made significant contributions. Table 1 summarizes the relevant articles reviewed in this study.

Table 1
Literature analysis surrounding Industry 4.0 and 5.0

Author(s) (Year)	Main Content
Singh, Yang and Park [12]	This study highlights various issues when IoT is applied to industrial infrastructure and proposes a solution called Fusion Fed Block, combining blockchain with federated learning to protect the privacy of Industry 5.0.
Li, Li, Ding, Ling and Huang [13]	This study introduces a method for safe human-machine interaction assisted by (Augmented Reality) AR in deep learning. It covers a range of safety measures for human-robot interaction, demonstrating the method's effectiveness through experimental results.
Karmaker, Ahmed, Ahmed, Ali, Moktadir and Kabir [17]	This study explores the impact of implementing Industry 5.0 on supply chain sustainability. The findings contribute to the understanding of supply chain sustainability and Industry 5.0, offering guidance and insights for supply chain management in the post-pandemic era.
Qahtan*, et al.* [24]	This study proposes a new electric vehicle benchmarking sustainable transportation modeling approach in the context of industry 5.0, incorporating Probabilistic Hesitant Fuzzy Set Fuzzy Weighted Zero-Inconsistency (PH-FWZIC) and the Multiplicative Multi-Objective Ratio Analysis Optimization (MULTIMOORA) decision model.
Nagy*, et al.* [25]	Utilizing the concept of intelligent spaces to support human-machine collaboration design in manufacturing, the study enhances collaboration among operators and provides them with information about their performance and the state of the production system.
Ghobakhloo, Iranmanesh, Mubarak, Mubarik, Rejeb and Nilashi [18]	This study formulates an Industry 5.0-driven sustainable development roadmap to better understand how Industry 5.0 contributes to sustainable development.
Orso, Ziviani, Bacchiega, Bondani, Spagnolli and Gamberini [22]	Highlighting the prioritization of worker welfare in Industry 5.0, the study adopts a mixed-method approach, combining employees' self-reports with event-based survey video analysis on-site, allowing for a comprehensive understanding of work activities and related major issues.
Khan*, et al.* [26]	Discussing the advantages of using backscatter communication and Non-Orthogonal Multiple Access (NOMA) in automotive Industry 5.0, the study proposes a multi-cell optimization framework to maximize the energy efficiency of NOMA-supported vehicular networks with backscatter.
Leng, Sha, Lin, Jing, Liu and Chen [16]	This study provides a comprehensive review of the evolution of Industry 5.0. The conclusion offers insights into the key drivers of Industry 5.0, future implementation pathways, potential applications, and challenges in real-world scenarios.
Ojstersek, Javernik and Buchmeister [21]	This study uses simulation modeling to discuss the impact of collaborative workplaces on manual assembly operations in production process bottlenecks. The study confirms the efficacy of collaborative workplaces as a practical solution.

Jan, Khan, Khan, Mastorakis, Menon, Alazab and Watters [10]	This study identifies Industry 5.0 as involving the digitalization, automation, and data exchange in industrial processes related to AI, industrial IoT, and Industrial Cyber-Physical Systems (I-CPS). It presents a lightweight mutual authentication scheme to address data privacy issues in healthcare.
Fraga-Lamas, Varela-Barbeito and Fernández-Caramés [23]	This study highlights that end-to-end transparency and human-centric traceability are key to achieving core aspects. Auto-ID technology plays a crucial role in automating item identification, localization, and tracking without human intervention or collaboration with industrial operators.
Tran, Ruppert, Eigner and Abonyi [20]	This study conducts a comprehensive system review of significant achievements in brownfield redevelopment projects. Based on this, it proposes practical management concepts and purposes, demonstrating their potential application in the production and operational decision-making process.
Sindhwani, Afridi, Kumar, Banaitis, Luthra and Singh [15]	This study introduces a multi-criteria analysis framework for assessing the drivers of Industry 5.0. Through case studies, it evaluates several enterprises implementing Industry 5.0, discussing their success factors and challenges, and summarizing lessons learned.
Melendez, Sima, Coudert, Geneste and de Valroger [14]	This study proposes an experience feedback method for human-centric collaborative modeling. It assesses and records collaboration then retrieves and reuses modeling for implementing new collaborations.
Richnák and Fidlerová [27]	The purpose of this study is to identify the collaborative potential of Industry 4.0 innovations and renewable energy initiatives in manufacturing and logistics, under the backdrop of sustainable development goals. The research summarizes the significant impact of environmental management on corporate production and logistics.
Pinciroli, Baraldi and Zio [19]	Highlighting a successful case, this study emphasizes the importance of utilizing Industry 4.0 technologies and data analysis for optimizing maintenance and improving manufacturing processes.

3. Methodology

This section explains the methodology proposed in this study. This study integrates FFs into the DEMATEL technique to retain a broader spectrum of potential, uncertain, or omitted information. The detailed conceptualization and computational procedure of the FF-DEMATEL method are described as follows:

Step 1: Establish an expert decision panel

An expert decision panel is formed by individuals who possess expertise relevant to the key factors that influence the successful development of Industry 5.0. Each expert in the panel, denoted as E_k (k = 1, 2,…, K) brings a unique perspective and expertise to the analysis.

Step 2: Build the semantic variables of FFs

All experts in the panel confirm and agree upon the key factors identified for this study. The factors C_j (j = 1, 2,…, n) are crucial for the successful development of Industry 5.0.

The assessment of interrelationships and influence among these factors can be conducted using the semantic variables provided in Table 2. The table shows that the "membership degree (μ)" reflects the extent to which the influence level, whereas the "non-membership degree (ν)"

represents the extent of irrelevance or insignificance. These FF values represent the uncertainty and vagueness inherent in human judgment, especially in assessing complex interrelations in the industrial environment. The use of such a detailed scale allows for a more precise and nuanced analysis of the influences among the key factors.

Table 2
Semantic variables of FFs [9]

Semantic variable	FF value	
Influence level	Membership (μ)	Non-membership (ν)
Near Influence (NI)	0.06	0.99
Low Influence (L)	0.11	0.99
Relatively Low Influence (RL)	0.27	0.98
Moderate Influence (M)	0.44	0.95
Moderately High Influence (MH)	0.56	0.90
High Influence (H)	0.69	0.82
Very High Influence (VH)	0.81	0.67
Extremely High Influence (EH)	0.92	0.51
Complete Influence (CI)	1.00	0.00

Step 3: Establish the FFs direct relation matrix.

The FF-DEMATEL calculation process involves establishing the FFs direct relation matrix in Step 3. This step is crucial for quantifying the direct influence strength among various factors as perceived by experts.

Experts are asked to conduct pairwise comparisons among *n* factors to determine the direct influence strength between them. Simplistically, expert *k* judges the direct influence of factor *i* on factor *j* on the base of a predefined scale, such as Table 2. Through the transformation of semantic variables, the FFs direct relation matrix can be obtained, as illustrated in Eq. (1).

$$\boldsymbol{X}^{(k)}=\begin{bmatrix} \left(\mu_F\left(x_{11}^{(k)}\right),\nu_F\left(x_{11}^{(k)}\right)\right) & \left(\mu_F\left(x_{12}^{(k)}\right),\nu_F\left(x_{12}^{(k)}\right)\right) & \cdots & \left(\mu_F\left(x_{1n}^{(k)}\right),\nu_F\left(x_{1n}^{(k)}\right)\right) \\ \left(\mu_F\left(x_{21}^{(k)}\right),\nu_F\left(x_{21}^{(k)}\right)\right) & \left(\mu_F\left(x_{22}^{(k)}\right),\nu_F\left(x_{22}^{(k)}\right)\right) & \cdots & \left(\mu_F\left(x_{2n}^{(k)}\right),\nu_F\left(x_{2n}^{(k)}\right)\right) \\ \vdots & \vdots & \ddots & \vdots \\ \left(\mu_F\left(x_{n1}^{(k)}\right),\nu_F\left(x_{n1}^{(k)}\right)\right) & \left(\mu_F\left(x_{n2}^{(k)}\right),\nu_F\left(x_{n2}^{(k)}\right)\right) & \cdots & \left(\mu_F\left(x_{nn}^{(k)}\right),\nu_F\left(x_{nn}^{(k)}\right)\right) \end{bmatrix} \tag{1}$$

$i = j = 1, 2, \ldots, n; k = 1, 2, \ldots, K.$

Here, $\mu_F\left(x_{ij}^{(k)}\right)$ and $\nu_F\left(x_{ij}^{(k)}\right)$ represent the membership and non-membership degrees that expert *k* assigns to the event *x*, respectively. The value range for $\mu_F\left(x_{ij}^{(k)}\right)$ and $\nu_F\left(x_{ij}^{(k)}\right)$ is [0, 1]. Importantly, the diagonal elements of the matrix must be zero, indicating no self-influence $\left(\mu_F\left(x_{ii}^{(k)}\right),\nu_F\left(x_{ii}^{(k)}\right)\right)=0$.

Additionally, in the context of FFs, the sum of the cubes of the membership and non-membership degrees is constrained to fall between 0 and 1, i.e., $0\le\left(\mu_F\left(x_{ij}^{(k)}\right)\right)^3+\left(\nu_F\left(x_{ij}^{(k)}\right)\right)^3\le 1$. Based on the definition of FFs, the degree of uncertainty for the assessment of expert *k* can be calculated using the Eq. (2)

$$\pi_F\left(x_{ij}^{(k)}\right)=\sqrt[3]{1-\left(\mu_F\left(x_{ij}^{(k)}\right)\right)^3-\left(v_F\left(x_{ij}^{(k)}\right)\right)^3},\ 0\le\pi_F\left(x_{ij}^{(k)}\right)\le 1. \tag{2}$$

Step 4: Construct the average FFs direct relation matrix

Integrating judgments from multiple experts to construct the average FFs direct relation matrix, as shown in Eq. (3)

$$A=\begin{bmatrix}\left(\mu_F\left(a_{11}\right),v_F\left(a_{11}\right)\right) & \left(\mu_F\left(a_{12}\right),v_F\left(a_{12}\right)\right) & \cdots & \left(\mu_F\left(a_{1n}\right),v_F\left(a_{1n}\right)\right)\\ \left(\mu_F\left(a_{21}\right),v_F\left(a_{21}\right)\right) & \left(\mu_F\left(a_{22}\right),v_F\left(a_{22}\right)\right) & \cdots & \left(\mu_F\left(a_{2n}\right),v_F\left(a_{2n}\right)\right)\\ \vdots & \vdots & \ddots & \vdots\\ \left(\mu_F\left(a_{n1}\right),v_F\left(a_{n1}\right)\right) & \left(\mu_F\left(a_{n2}\right),v_F\left(a_{n2}\right)\right) & \cdots & \left(\mu_F\left(a_{nn}\right),v_F\left(a_{nn}\right)\right)\end{bmatrix},\ i=j=1,2,\ldots,n. \tag{3}$$

where $\left(\mu_F\left(a_{ij}\right),v_F\left(a_{ij}\right)\right)=\dfrac{\sum_{k=1}^{K}\left(\mu_F\left(x_{11}^{(k)}\right),v_F\left(x_{11}^{(k)}\right)\right)}{k}$.

Step 5: Calculate the f-score and obtain the initial relation matrix

This step is crucial for quantifying the overall uncertainty inherent in the expert judgments and ensuring the robustness of the analysis. The calculation of the average f-score of FFs is based on the rules established by Senapati and Yager [28]. These rules provide a systematic approach to derive the average f-scores of FFs, as shown in Eq. (4)

$$score\,f\left(\mu_F\left(a_{ij}\right),v_F\left(a_{ij}\right)\right)=\left(\mu_F\left(a_{ij}\right)\right)^3-\left(v_F\left(a_{ij}\right)\right)^3,$$

$$-1\le score\,f\left(\mu_F\left(a_{ij}\right),v_F\left(a_{ij}\right)\right)\le 1. \tag{4}$$

The f-scores, as initially calculated, are within the range of [-1,1]. While this range is mathematically valid, it may not be immediately intuitive for practical decision-making and comparative analysis. To make them more usable, a normalization process is employed. Defuzzification thus serves as a crucial step in converting the nuanced and fuzzy data into a more definitive and comprehensible format, as shown in Eq. (5).

$$\varphi_{ij}=1+score\,f\left(\mu_F\left(a_{ij}\right),v_F\left(a_{ij}\right)\right),\ 0\le\varphi_{ij}\le 1. \tag{5}$$

Thus, the initial relation matrix of FF-DEMATEL is as presented in Eq. (6)

$$\boldsymbol{\varphi}=\begin{bmatrix}\varphi_{11} & \varphi_{12} & \cdots & \varphi_{1n}\\ \varphi_{21} & \varphi_{22} & \cdots & \varphi_{2n}\\ \vdots & \vdots & \ddots & \vdots\\ \varphi_{n1} & \varphi_{n2} & \cdots & \varphi_{nn}\end{bmatrix},\ i=j=1,2,\ldots,n. \tag{6}$$

Step 6: Obtain the normalized relation matrix

Subsequently, the conventional operations of the DEMATEL method are followed. a normalization procedure is executed to obtain the normalized relation matrix, as shown in Eq. (7)

$$\boldsymbol{\gamma} = \begin{bmatrix} \varepsilon \cdot \varphi_{11} & \varepsilon \cdot \varphi_{12} & \cdots & \varepsilon \cdot \varphi_{1n} \\ \varepsilon \cdot \varphi_{21} & \varepsilon \cdot \varphi_{22} & \cdots & \varepsilon \cdot \varphi_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \varepsilon \cdot \varphi_{n1} & \varepsilon \cdot \varphi_{n2} & \cdots & \varepsilon \cdot \varphi_{nn} \end{bmatrix},\ i = j = 1, 2, \ldots, n. \tag{7}$$

where $\varepsilon = \dfrac{1}{\max\left\{\sum_{j=1}^{n} \varphi_{ij}, \sum_{i=1}^{n} \varphi_{ij}\right\}}$.

Step 7: Generate the total influence matrix

The interrelationships among factors can be either direct and indirect. To ensure that all potential influences are accounted for, the matrix is subjected to self-multiplication and subsequent accumulation, as shown in Eq. (8) This process results in the the total influence matrix, as shown in Eq. (9).

$$\begin{aligned} \boldsymbol{T} &= \boldsymbol{\gamma} + \boldsymbol{\gamma}^2 + \boldsymbol{\gamma}^3 + \cdots \boldsymbol{\gamma}^{\infty} = \boldsymbol{\gamma}\left(\boldsymbol{I} + \boldsymbol{\gamma} + \boldsymbol{\gamma}^2 + \boldsymbol{\gamma}^3 + \cdots + \boldsymbol{\gamma}^{\infty-1}\right) \\ &= \boldsymbol{\gamma}\left(\boldsymbol{I} - \boldsymbol{\gamma}^{\infty}\right)\left(\boldsymbol{I} - \boldsymbol{\gamma}\right)^{-1} = \boldsymbol{\gamma}\left(\boldsymbol{I} - \boldsymbol{\gamma}\right)^{-1} \end{aligned} \tag{8}$$

while ***I*** denotes the identity matrix.

$$\boldsymbol{T} = \begin{bmatrix} t_{11} & t_{12} & \cdots & t_{1n} \\ t_{21} & t_{22} & \cdots & t_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ t_{n1} & t_{n2} & \cdots & t_{nn} \end{bmatrix},\ i = j = 1, 2, \ldots, n. \tag{9}$$

Step 8: Obtaine the weights of the factors and build the INRM

The elements of $\boldsymbol{T}$ can be interpreted as the sum of the direct and indirect influences of factor *i* on factor *j*. Consequently, the influence degree of factor *i*, denoted as "r_i", can be obtained using Eq. (10). Similarly, the degree to which factor *i* is influenced, denoted as "s_i" is calculated as per Eq. (11).

$$r_i = t_{11} + t_{12} + \cdots t_{1n} = \sum_{j=1}^{n} t_{ij} \tag{10}$$

$$s_i = t_{11} + t_{21} + \cdots t_{n1} = \left[\sum_{i=1}^{n} t_{ij}\right]^{Transpose} \tag{11}$$

The total influence of a factor, which encompasses both r_i and s_i, can be defined as $r_i + s_i$. The influence weight of factor *i* within the assessment system can then be obtained through Eq. (12).

$$w_i = \frac{r_i + s_i}{\sum_{i=1}^{n}\left(r_i + s_i\right)} \tag{12}$$

On the other hand, $r_i - s_i$ reflects the net influence of factor *i*. By using $r_i + s_i$ and $r_i - s_i$ as the horizontal and vertical axes, respectively, the relative position of each factor can be delineated in the INRM.

4. Experimental Analysis

4.1 Evaluation framework for industrial 5.0 development

This evaluation framework for Industrial 5.0 development is divided into three dimensions: Human-Centricity (D_1), Process Flexibility (D_2), and Sustainable Development (D_3). Under these dimensions, there are a total of 18 factors. These include: Comprehensive Automation Testing (F_1), Data-Driven Analysis Technologies (F_2), Human-Robot Collaboration (F_3), Cross-Departmental Organizational Integration (F_4), Real-Time Information Sharing (F_5), Bionics (F_6), Distributed Control (F_7), Intelligent Manufacturing (F_8), Structural Adjustment (F_9), Mass Customization (F_{10}), Supply Chain Flexibility (F_{11}), Lean Production (F_{12}), Remanufacturing (F_{13}), Renewable Energy (F_{14}), Circular Economy (F_{15}), Green and Environmental Protection (F_{16}), Smart Components (F_{17}), and Product Lifecycle Management (F_{18}). These factors are derived from the literature review mentioned in Section 2 and were established after multiple discussions with experts. The classification and detailed descriptions of these factors can be found in Table 3.

Table 3
Key factors for the successful development of Industry 5.0

Dimension	Factor	Description
Human-Centricity (D_1)	Comprehensive Automation Testing (F_1)	Achieving automation in production processes to enhance operational efficiency and obtain real-time data.
	Data-Driven Analysis Technologies (F_2)	Utilizing technologies such as IoT, cloud computing, big data, and AI to assist enterprises in handling large volumes of real-time data.
	Human-Robot Collaboration(F_3)	Achieving collaboration with cobots to make them more active for people working nearby.
	Cross-Departmental Organizational Integration (F_4)	Applying multi-disciplinary cross-professional knowledge to redesign human-centric interconnected systems.
	Real-Time Information Sharing (F_5)	Supporting the development of Industry 5.0 through real-time operating systems, software engineering, and other technological equipment.
	Bionics (F_6)	Developing related technologies and knowledge for collaborative robots: bionics, augmented reality, ergonomics, etc.
Process Flexibility (D_2)	Distributed Control (F_7)	Achieving distributed control through cutting-edge technologies like deep learning and edge computing to increase operational flexibility.
	Intelligent Manufacturing (F_8)	Enhancing productivity and efficiency through smart materials, intelligent systems, etc., to achieve intelligent manufacturing.
	Structural Adjustment (F_9)	Implementing structural adjustments to delay the formation or delivery of final products, thereby reducing operational risks.
	Mass Customization (F_{10})	Achieving mass customization to meet goals of high efficiency, quality, and low cost.

Dimension	Factor	Description
	Supply Chain Flexibility (F_{11})	Increasing supply chain flexibility to enhance the controllability of operational processes, addressing failures or disruptions in the supply chain.
	Lean Production (F_{12})	Assisting enterprises in achieving lean production through rapid tooling changes, data visualization management, etc., for effective management.
Sustainable Development (D_3)	Remanufacturing (F_{13})	Restoring high-value end-of-life (EOL) products through remanufacturing, reducing waste generation and resource loss, thereby cutting costs.
	Renewable Energy (F_{14})	Utilizing renewable and bioenergy to achieve carbon emission reduction goals and realize a low-carbon environment.
	Circular Economy (F_{15})	Promoting the circular economy to achieve reductions in resource input and waste emissions, protecting ecological and resource integrity.
	Green and Environmental Protection (F_{16})	Implementing solutions for climate change through ecological innovation, achieving the vision of green environmental protection.
	Smart Components (F_{17})	Effectively utilizing emerging and enabling technologies through smart components to promote sustainable development in enterprises.
	Product Lifecycle Management (F_{18})	Achieving operational efficiency with minimized resource use through product lifecycle management, reducing waste to protect the environment.

4.2 Expert Backgrounds and Questionnaire Collection

This study's data collection was primarily conducted through a small, specialized, and representative sample of experts, as opposed to large-scale surveys with general questionnaires. The scope of the questionnaire distribution was targeted within the Taiwanese industrial, governmental, academic, and research sectors, with a specific focus on the electronics manufacturing industry. To ensure the reliability and credibility of the data sources for this study, a decision panel of 17 experts was assembled. Their representativeness in their respective fields was scrutinized in confirming experts based on their backgrounds. Multiple video conference discussions were held with each expert to ensure a smooth and accurate completion of the FF-DEMATEL questionnaire.

Given that the study's data collection was based on a small expert decision group, stringent scrutiny of the data accuracy was required. To ensure the validity of the research, the selected members of the expert decision panel were all decision-makers, executives, and even CEOs of their respective companies, all holding at least a master's degree and possessing over ten years of professional experience in their fields. The details of the experts are presented in Table 4.

Table 4
Information on the Expert Panel

No.	Gender	Education	Age	Category	Job Title	Work Experience
1	Male	Ph.D.	55	Industry	Sales Manager	Over 20 years
2	Male	Ph.D.	58	Industry	Director	Over 30 years
3	Male	Ph.D.	63	Industry	General Manager	Over 30 years
4	Male	Master	58	Industry	Plant Manager	Over 30 years
5	Male	Master	62	Industry	CEO	Over 30 years
6	Female	Ph.D.	63	Industry	Deputy General Manager	Over 30 years
7	Male	Ph.D.	52	Academia	Professor	Over 10 years
8	Male	Ph.D.	56	Academia	Professor	Over 20 years
9	Male	Ph.D.	50	Academia	Professor	Over 20 years
10	Male	Master	56	Institutional	Vice Chairman	Over 30 years
11	Male	Master	58	Institutional	Chairman	Over 30 years
12	Male	Ph.D.	60	Institutional	Assistant Manager	Over 30 years
13	Male	Master	60	Institutional	Deputy Manager	Over 30 years
14	Male	Master	41	Institutional	Senior Engineer	Over 15 years
15	Male	Ph.D.	54	Institutional	Senior Engineer	Over 30 years
16	Male	Master	46	Institutional	Senior Engineer	Over 20 years
17	Male	Master	42	Institutional	Senior Engineer	Over 10 years

This study converted the collected data into semantic terms upon completing all data collection. Subsequently, it carried out the weight calculation of the influence of key factors for the successful development of Industry 5.0 using the FF-DEMATEL. Before the experts complete the questionnaire, we first introduce the basic concepts of FF-DEMATEL. Then, we provide one-on-one guidance to assist each expert in assessing the influence of these factors.

4.3 Implementation of FF-DEMATEL

Here, we illustrate using the FFs direct relation matrix from the first expert as an example. The first expert evaluates the impact of all dimensions and factors, recording their judgments in semantic terms, as shown in Table 5.

Table 5
The FFs direct relation matrix by the first expert

	D_1	D_2	D_3			
D_1	0	H	EH			
D_2	M	0	H			
D_3	EH	EH	0			
	F_1	F_2	F_3	F_4	F_5	F_6
F_1	0	EH	L	M	H	L
F_2	EH	0	EH	H	EH	H
F_3	M	H	0	M	M	H
F_4	EH	M	H	0	M	M
F_5	EH	EH	M	M	0	M
F_6	M	M	M	EH	M	0

	F_7	F_8	F_9	F_{10}	F_{11}	F_{12}
F_7	0	EH	EH	M	M	M
F_8	H	0	EH	M	M	H
F_9	EH	M	0	M	H	M
F_{10}	M	H	M	0	EH	M
F_{11}	M	M	M	M	0	EH
F_{12}	H	M	M	M	M	0
	F_{13}	F_{14}	F_{15}	F_{16}	F_{17}	F_{18}
F_{13}	0	EH	H	H	H	H
F_{14}	M	0	EH	EH	H	H
F_{15}	H	EH	0	EH	M	EH
F_{16}	H	H	H	0	EH	M
F_{17}	H	EH	M	H	0	EH
F_{18}	M	EH	EH	H	H	0

The degree of uncertainty for each expert during the evaluation process is obtained through Eq. (2). The data from multiple experts who have completed the questionnaire is integrated using Eq. (3). This integration involves calculating the arithmetic mean of each factor to form the average FFs direct relation matrix, as shown in Table 6.

Table 6
The average FFs direct relation matrix

	D_1	D_2	D_3			
D_1	0	(0.688,0.792)	(0.884,0.443)			
D_2	(0.570,0.882)	0	(0.769,0.671)			
D_3	(0.931,0.306)	(0.931,0.306)	0			
	F_1	F_2	F_3	F_4	F_5	F_6
F_1	0	(0.931,0.306)	(0.363,0.945)	(0.526,0.905)	(0.746,0.749)	(0.419,0.935)
F_2	(0.919,0.346)	0	(0.919,0.346)	(0.746,0.749)	(0.933,0.328)	(0.746,0.749)
F_3	(0.511,0.913)	(0.746,0.749)	0	(0.526,0.905)	(0.526,0.905)	(0.746,0.749)
F_4	(0.933,0.328)	(0.526,0.905)	(0.746,0.749)	0	(0.541,0.898)	(0.541,0.898)
F_5	(0.906,0.364)	(0.944,0.288)	(0.526,0.905)	(0.52,0.905)	0	(0.526,0.905)
F_6	(0.526,0.905)	(0.526,0.905)	(0.541,0.898)	(0.933,0.328)	(0.526,0.905)	0
	F_7	F_8	F_9	F_{10}	F_{11}	F_{12}
F_7	0	(0.958,0.270)	(0.958,0.270)	(0.526,0.905)	(0.541,0.898)	(0.541,0.898)
F_8	(0.644,0.826)	0	(0.958,0.270)	(0.570,0.876)	(0.541,0.898)	(0.629,0.834)
F_9	(0.958,0.270)	(0.526,0.905)	0	(0.526,0.905)	(0.585,0.863)	(0.541,0.898)
F_{10}	(0.526,0.905)	(0.658,0.813)	(0.526,0.905)	0	(0.807,0.595)	(0.541,0.898)
F_{11}	(0.614,0.842)	(0.511,0.919)	(0.511,0.919)	(0.511,0.919)	0	(0.958,0.270)
F_{12}	(0.658,0.813)	(0.526,0.905)	(0.526,0.905)	(0.585,0.863)	(0.599,0.855)	0
	F_{13}	F_{14}	F_{15}	F_{16}	F_{17}	F_{18}
F_{13}	(0.000,0.000)	(0.958,0.270)	(0.717,0.765)	(0.746,0.749)	(0.834,0.558)	(0.732,0.757)
F_{14}	(0.644,0.821)	(0.000,0.000)	(0.958,0.270)	(0.958,0.270)	(0.834,0.558)	(0.732,0.757)
F_{15}	(0.717,0.765)	(0.958,0.270)	(0.000,0.000)	(0.958,0.270)	(0.511,0.919)	(0.958,0.270)
F_{16}	(0.746,0.749)	(0.746,0.749)	(0.717,0.765)	(0.000,0.000)	(0.958,0.270)	(0.511,0.919)
F_{17}	(0.732,0.757)	(0.958,0.270)	(0.496,0.926)	(0.717,0,778)	(0.000,0.000)	(0.958,0.270)
F_{18}	(0.585,0.863)	(0.958,0.270)	(0.958,0.270)	(0.702,0.778)	(0.702,0.778)	(0.000,0.000)

Applying Eq. (4) and Eq. (5), the process of defuzzification is performed to obtain the f-scores. Based on Eq. (6), the initial relation matrix of FF-DEMATEL is constructed, as presented in Table 7. Next, the calculation process follows the Section 3.

By applying Eqs. (7) to (12), the results of the FF-DEMATEL analysis are obtained, as shown in Table 8. Since the perspective of examining key factors is divided into three dimensions, the weights within each dimension are used as indices for ranking.

Table 7
The initial relation matrix

	D_1	D_2	D_3			
D_1	0.000	0.829	1.603			
D_2	0.498	0.000	1.153			
D_3	1.777	1.777	0.000			
	F_1	F_2	F_3	F_4	F_5	F_6
F_1	0.000	1.777	0.205	0.403	0.995	0.255
F_2	1.736	0.000	1.736	0.995	1.777	0.995
F_3	0.373	0.995	0.000	0.403	0.403	0.995
F_4	1.777	0.403	0.995	0.000	0.435	0.435
F_5	1.695	1.818	0.403	0.403	0.000	0.403
F_6	0.403	0.403	0.435	1.777	0.403	0.000
	F_7	F_8	F_9	F_{10}	F_{11}	F_{12}
F_7	0.000	1.859	1.859	0.403	0.435	0.435
F_8	0.702	0.000	1.859	0.512	0.435	0.668
F_9	1.859	0.403	0.000	0.403	0.557	0.435
F_{10}	0.403	0.748	0.403	0.000	1.315	0.435
F_{11}	0.635	0.358	0.358	0.358	0.000	1.859
F_{12}	0.748	0.403	0.403	0.557	0.590	0.000
	F_{13}	F_{14}	F_{15}	F_{16}	F_{17}	F_{18}
F_{13}	0.000	1.859	0.922	0.995	1.406	0.958
F_{14}	0.714	0.000	1.859	1.859	1.406	0.958
F_{15}	0.922	1.859	0.000	1.859	0.358	1.859
F_{16}	0.995	0.995	0.922	0.000	1.859	0.358
F_{17}	0.958	1.859	0.327	0.922	0.000	1.859
F_{18}	0.557	1.859	1.859	0.875	0.875	0.000

Table 8
The results of the FF-DEMATEL analysis

	r	s	$r + s$	$r - s$	Weight	Rank
D_1	2.555	2.348	4.903	0.208	0.324	2
D_2	1.824	2.597	4.422	-0.773	0.292	3
D_3	3.190	2.624	5.814	0.566	0.384	1
F_1	1.534	2.152	3.686	-0.619	0.190	2
F_2	2.476	2.005	4.481	0.471	0.230	1
F_3	1.205	1.430	2.635	-0.224	0.135	5
F_4	1.438	1.397	2.835	0.041	0.146	4
F_5	1.845	1.577	3.422	0.268	0.176	3
F_6	1.228	1.164	2.392	0.064	0.123	6

F_7	4.174	3.764	7.938	0.410	0.212	1
F_8	3.455	3.223	6.678	0.232	0.178	3
F_9	3.304	4.151	7.455	-0.848	0.199	2
F_{10}	2.735	1.940	4.675	0.796	0.125	6
F_{11}	2.779	2.623	5.403	0.156	0.144	4
F_{12}	2.308	3.054	5.362	-0.746	0.143	5
F_{13}	2.762	1.930	4.692	0.832	0.142	6
F_{14}	2.986	3.557	6.542	-0.571	0.198	1
F_{15}	3.014	2.703	5.718	0.311	0.173	2
F_{16}	2.330	2.967	5.296	-0.637	0.160	5
F_{17}	2.657	2.711	5.368	-0.054	0.162	4
F_{18}	2.780	2.660	5.440	0.120	0.165	3

The INRM can be plotted using $r+s$ as the horizontal axis and $r-s$ as the vertical axis. In this context, $r+s$ represents the total influence. The higher its value, the more significant the factor in the assessment system. Conversely, $r-s$ represents the net influence; a positive net influence indicates that the key factor has a stronger direct influence relationship, while a negative net influence suggests a stronger indirect influence relationship. The INRM constructed in this study allows decision-makers to quickly understand which factors are influential and which are more susceptible to influence by others. The specific managerial implications of this are discussed in greater detail in the next section.

5. Discussion

This section presents the research findings and visualizes the analyzed data through the INRM, providing insights for corporate decision-makers. Table 8 displays the overall ranking of factors and their active and passive influence intensities. The interrelationships among the other factors are also visually represented in the INRM, as shown in Figure 1.

Figure 1 illustrates the interrelationships among the key factors. This study has six specific managerial implications, which are detailed below.

i. Among the three important dimensions in developing Industry 5.0, “Sustainable Development (D_3)” significantly influences “Human-Centricity (D_1)” and “Process Flexibility (D_2).” Chang*, et al.* [29] highlighted that the electronics manufacturing industry is an Energy-Intensive Industry (EII). While the energy supply chain can drive economic and social development, greenhouse gas emissions from manufacturing processes affect outdoor temperatures and air quality. Additionally, the burial and incineration of electronic waste produce chemicals that pose environmental threats. Therefore, sustainability is the most important dimension to consider when developing Industry 5.0 for the electronics manufacturing industry.

ii. “Renewable Energy (F_{14})” significantly influences other factors within the Sustainable Development (D_3) dimension. Carbon reduction is a crucial issue in achieving sustainable development, and carbon emissions are a critical indicator used by countries worldwide to measure whether a company's processes are sustainable. For instance, the EU’s Carbon Border Adjustment Mechanism, the USA’s Clean Competition Act, and Taiwan's Climate Change Act all use carbon emissions as a measure of sustainability. In Taiwan’s electronics manufacturing industry, companies tend to purchase electricity as a means of carbon offsetting, which is why renewable energy is prioritized over other factors.

iii. (iii) From the perspective of Human-centrism (D_1), “Data-Driven Analysis Technologies (F_2)” significantly influences other factors. This technology is an extensive data-based method that processes and analyzes large data sets to gain deeper insights. In Taiwan's electronics manufacturing industry, companies use data-driven analysis to analyze human and machine behaviors, better identify overall patterns, habits, or anomalies, and promptly discover potential problems in collaboration.

iv. (iv) In the dimension of Process Flexibility (D_2), "Distributed Control (F_7)" and "Intelligent Manufacturing (F_8)" are greatly influential. The use of Programmable Logic Controllers (PLCs) is crucial for Taiwan's electronics manufacturing industry. Enterprises can collect production data through sensors and PLCs, allowing machines, peripherals, and components to self-sense and regulate, thus maintaining consistency in quality. Therefore, when facing bottleneck issues that require a rapid response, distributed control can more efficiently assess the current situation and formulate strategies to minimize losses. In Taiwan's electronics manufacturing, intelligent manufacturing is used to enhance product precision and reliability. Enterprises can predict and prevent potential production issues while reducing operational risks and increasing productivity, efficiency, and quality by utilizing AI and big data technologies.

v. Among all key factors, "Cross-Departmental Organizational Integration (F_4)," "Bionics (F_6)," "Mass Customization (F_{10})," "Supply Chain Flexibility (F_{11})," and "Lean Production (F_{12})" are independent because they do not have a significant influence on the other factors and vice versa.

In addition to examining the INRM, company decision-makers and management executives can also review the overall ranking and global weight of each factor, as shown in Table 9. Firstly, it aids in strategic prioritization, allowing decision-makers to allocate resources effectively to the most influential factors. By identifying criteria with higher weights or ranks, key areas needing improvement are highlighted, thereby facilitating targeted action. Moreover, The clear and quantifiable nature of this ranking system also streamlines communication and alignment across different departments, ensuring unified efforts towards shared goals. Lastly, regular analysis of these factors supports agile adaptation to business environment changes, by pinpointing areas most susceptible to shifts.

Table 9
Overall tanking and Global weight of factors

Factor	$r + s$	Local weight	Rank	Global weight	Rank
D_1	4.925	0.321	2		
D_2	4.496	0.293	3		
D_3	5.909	0.385	1		
F_1	3.669	0.190	2	0.061	8
F_2	4.469	0.231	1	0.074	2
F_3	2.614	0.135	5	0.043	14
F_4	2.810	0.145	4	0.047	13
F_5	3.409	0.176	3	0.057	10
F_6	2.360	0.122	6	0.039	17
F_7	8.093	0.212	1	0.062	5
F_8	6.791	0.178	3	0.052	12
F_9	7.570	0.199	2	0.058	9
F_{10}	4.723	0.124	6	0.036	18
F_{11}	5.469	0.144	4	0.042	15
F_{12}	5.439	0.143	5	0.042	16

Factor	$r + s$	Local weight	Rank	Global weight	Rank
F_{13}	4.620	0.142	6	0.055	11
F_{14}	6.459	0.198	1	0.077	1
F_{15}	5.656	0.174	2	0.067	3
F_{16}	5.219	0.160	5	0.062	7
F_{17}	5.260	0.162	4	0.062	6
F_{18}	5.333	0.164	3	0.063	4

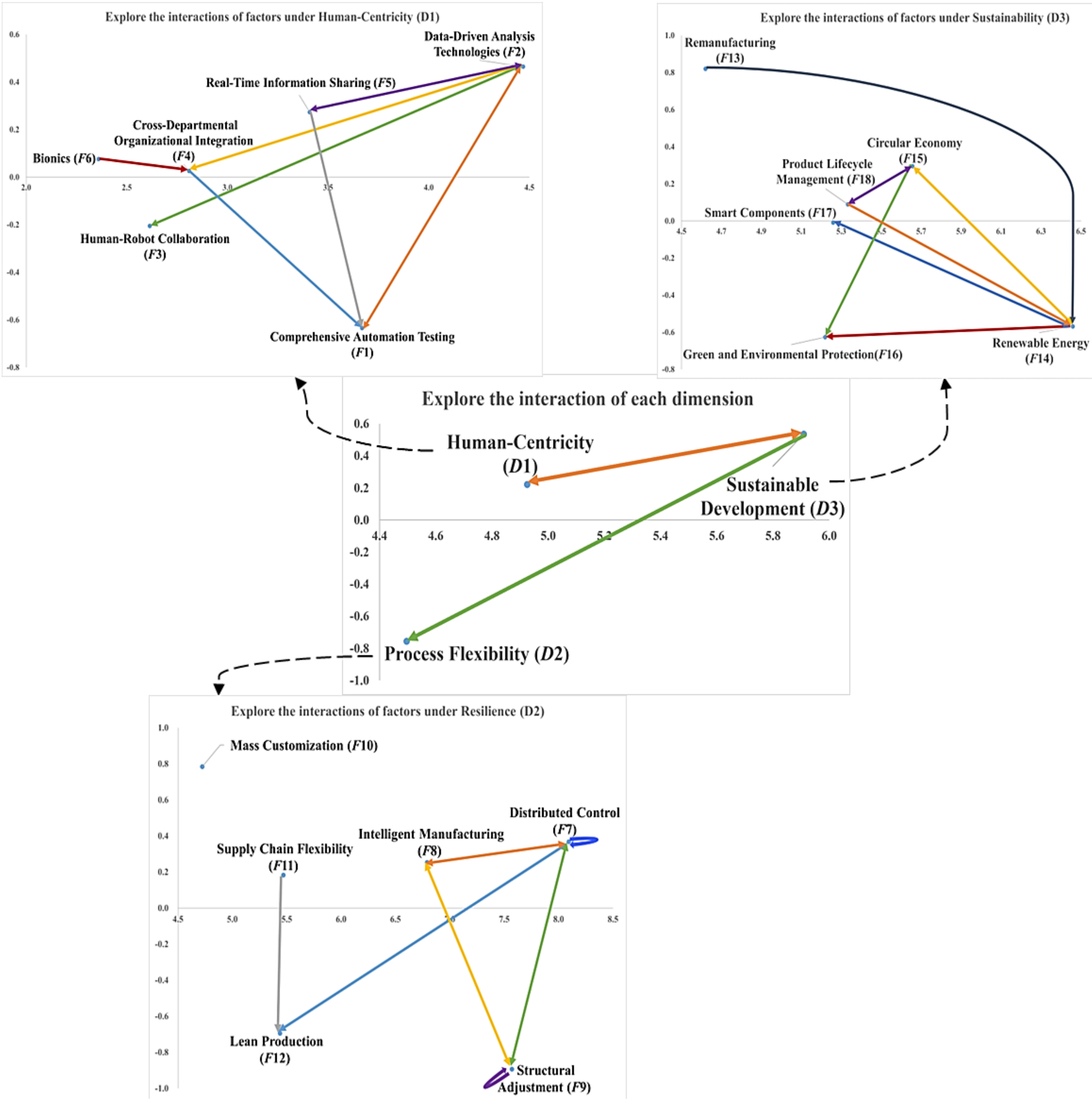

Fig. 1. The INRM of the successful development factors of Industry 5.0

6. Conclusions

This study aims to fill a critical research gap in what is already known by systematically examining how these three key dimensions and 18 facotrs of Industry 5.0 interact. The FF-DEMATEL technique helps to understand how different variables interact within a dynamic industrial ecosystem. It was used for the research, providing several advantages. FF-DEMATEL is adept at handling the ambiguities and complexities inherent in industrial systems, particularly as they manifest in the context of Industry 5.0. This capability allows for a more nuanced and accurate analysis of these systems. This approach captures subtleties missed by traditional analysis methods that appear insignificant but are important. Secondly, the method's capacity to trace cause-and-effect relationships among various factors provides a clear and complete understanding of their interrelationships.

Using weight ranking, businesses can facilitate the formulation of strategies related to the development of Industry 5.0. For instance, the results of this study distinctly highlight the technical competencies required for the development of Industry 5.0, which can be used to guide human resource training. Additionally, companies can allocate their budget based on the ranking of each factor to minimize the risk of failure while enhancing long-term competitiveness. In time planning, the overall weight and ranking of the 18 key factors presented in this study can serve as a basis for companies to devise their Industry 5.0 development strategies.

Many previous studies have proposed a vision for the development of Industry 5.0. However, most research methodologies consider factors as independent and unrelated. This study posits that the key factors of Industry 5.0 are interdependently restrictive. Nonetheless, this research has certain limitations. Firstly, the factors influencing the development of Industry 5.0 are not limited to the 18 listed in this study. The key factors are not static and can be further subdivided. Secondly, this study focuses primarily on Taiwan's electronics manufacturing industry. The anticipated problems and analytical results are based solely on this industry’s context, which may not be applicable to other industries or domains. Consequently, the research findings and managerial implications may not align with the situation of all industries. Lastly, since the data collection in FF-DEMATEL is based on a small sample of experts, it is imperative to ensure the rigor of the data to guarantee the quality and feasibility of the research.

Author Contributions

Conceptualization, H.-W.C. and J.-W.L.; methodology, H.-W.L.; software, H.-W.L.; validation, H.-W.C. and J.-W.L. and S.-W.L.; formal analysis, H.-W.C. and J.-W.L. and S.-W.L.; investigation, H.-W.C. and J.-W.L.; resources, H.-W.L.; data curation, H.-W.L.; writing—original draft preparation, S.-W.L.; writing—review and editing, H.-W.L.; visualization, H.-W.C. and J.-W.L.; supervision, S.-W.L.; project administration, H.-W.L. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

There is no data in this study.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] Destouet, C., Tlahig, H., Bettayeb, B. & Mazari, B. (2023). Flexible job shop scheduling problem under Industry 5.0: A survey on human reintegration, environmental consideration and resilience improvement. *Journal of Manufacturing Systems*, *67*, 155-173. https://doi.org/10.1016/j.jmsy.2023.01.004

[2] Ahmed, T., Karmaker, C. L., Nasir, S. B., Moktadir, M. A. & Paul, S. K. (2023). Modeling the artificial intelligence-based imperatives of industry 5.0 towards resilient supply chains: A post-COVID-19 pandemic perspective. *Computers & Industrial Engineering*, *177*, 109055. https://doi.org/10.1016/j.cie.2023.109055

[3] Leng, J., Sha, W., Wang, B., Zheng, P., Zhuang, C., Liu, Q., Wuest, T., Mourtzis, D. & Wang, L. (2022). Industry 5.0: Prospect and retrospect. *Journal of Manufacturing Systems*, *65*, 279-295. https://doi.org/10.1016/j.jmsy.2022.09.017

[4] Lu, Y., Zheng, H., Chand, S., Xia, W., Liu, Z., Xu, X., Wang, L., Qin, Z. & Bao, J. (2022). Outlook on human-centric manufacturing towards Industry 5.0. *Journal of Manufacturing Systems*, *62*, 612-627. https://doi.org/10.1016/j.jmsy.2022.02.001

[5] Kasinathan, P., Pugazhendhi, R., Elavarasan, R. M., Ramachandaramurthy, V. K., Ramanathan, V., Subramanian, S., Kumar, S., Nandhagopal, K., Raghavan, R. R. V. & Rangasamy, S. (2022). Realization of Sustainable Development Goals with Disruptive Technologies by Integrating Industry 5.0, Society 5.0, Smart Cities and Villages. *Sustainability*, *14*(22), 15258. https://doi.org/10.3390/su142215258

[6] Dwivedi, A., Agrawal, D., Jha, A. & Mathiyazhagan, K. (2023). Studying the interactions among Industry 5.0 and circular supply chain: Towards attaining sustainable development. *Computers & Industrial Engineering*, *176*, 108927. https://doi.org/10.1016/j.cie.2022.108927

[7] Chang, C.-C., Pai, C.-J. & Lo, H.-W. (2023). Sustainable Development Evaluation of Cultural and Creative Industries Using a Neutrosophic-Based Dematel–Topsis Approach. *International Journal of Information Technology & Decision Making*, 1-34. https://doi.org/10.1142/S0219622023500426

[8] Gul, M., Lo, H.-W. & Yucesan, M. (2021). Fermatean fuzzy TOPSIS-based approach for occupational risk assessment in manufacturing. *Complex & Intelligent Systems*, *7*, 2635-2653. https://doi.org/10.1007/s40747-021-00417-7

[9] Kao, F.-C., Huang, S.-C. & Lo, H.-W. (2022). A rough-fermatean DEMATEL approach for sustainable development evaluation for the manufacturing industry. *International Journal of Fuzzy Systems*, *24*(7), 3244-3264. https://doi.org/10.1007/s40815-022-01334-8

[10] Jan, M. A., Khan, F., Khan, R., Mastorakis, S., Menon, V. G., Alazab, M. & Watters, P. (2020). Lightweight mutual authentication and privacy-preservation scheme for intelligent wearable devices in industrial-CPS. *IEEE transactions on industrial informatics*, *17*(8), 5829-5839. https://doi.org/10.1109/TII.2020.3043802

[11] Zhang, C., Wang, Z., Zhou, G., Chang, F., Ma, D., Jing, Y., Cheng, W., Ding, K. & Zhao, D. (2023). Towards new-generation human-centric smart manufacturing in Industry 5.0: A systematic review. *Advanced Engineering Informatics*, *57*, 102121. https://doi.org/10.1016/j.aei.2023.102121

[12] Singh, S. K., Yang, L. T. & Park, J. H. (2023). FusionFedBlock: Fusion of blockchain and federated learning to preserve privacy in industry 5.0. *Information Fusion*, *90*, 233-240. https://doi.org/10.1016/j.inffus.2022.09.027

[13] Li, M., Li, M., Ding, H., Ling, S. & Huang, G. Q. (2022). Graduation-inspired synchronization for industry 4.0 planning, scheduling, and execution. *Journal of Manufacturing Systems*, *64*, 94-106. https://doi.org/10.1016/j.jmsy.2022.05.017

[14] Melendez, S., Sima, X., Coudert, T., Geneste, L. & de Valroger, A. (2022). An experience feedback process for learning from collaboration experiences. *Computers in Industry*, *141*, 103693. https://doi.org/10.1016/j.compind.2022.103693

[15] Sindhwani, R., Afridi, S., Kumar, A., Banaitis, A., Luthra, S. & Singh, P. L. (2022). Can industry 5.0 revolutionize the wave of resilience and social value creation? A multi-criteria framework to analyze enablers. *Technology in Society*, *68*, 101887. https://doi.org/10.1016/j.techsoc.2022.101887

[16] Leng, J., Sha, W., Lin, Z., Jing, J., Liu, Q. & Chen, X. (2023). Blockchained smart contract pyramid-driven multi-agent autonomous process control for resilient individualised manufacturing towards Industry 5.0. *International Journal of Production Research*, *61*(13), 4302-4321. https://doi.org/10.1080/00207543.2022.2089929

[17] Karmaker, C. L., Ahmed, T., Ahmed, S., Ali, S. M., Moktadir, M. A. & Kabir, G. (2021). Improving supply chain sustainability in the context of COVID-19 pandemic in an emerging economy: Exploring drivers using an integrated model. *Sustainable production and consumption*, *26*, 411-427. https://doi.org/10.1016/j.spc.2020.09.019

[18] Ghobakhloo, M., Iranmanesh, M., Mubarak, M. F., Mubarik, M., Rejeb, A. & Nilashi, M. (2022). Identifying industry 5.0 contributions to sustainable development: A strategy roadmap for delivering sustainability values. *Sustainable Production and Consumption*, *33*, 716-737. https://doi.org/10.1016/j.spc.2022.08.003

[19] Pinciroli, L., Baraldi, P. & Zio, E. (2023). Maintenance optimization in Industry 4.0. *Reliability Engineering & System Safety*, 109204. https://doi.org/10.1016/j.ress.2023.109204

[20] Tran, T.-A., Ruppert, T., Eigner, G. & Abonyi, J. (2022). Retrofitting-based development of brownfield industry 4.0 and industry 5.0 solutions. *IEEE Access*, *10*, 64348-64374. https://doi.org/10.1109/ACCESS.2022.3182491

[21] Ojstersek, R., Javernik, A. & Buchmeister, B. (2021). The impact of the collaborative workplace on the production system capacity: Simulation modelling vs. real-world application approach. *Advances in Production Engineering & Management*, *16*(4), 431-442. https://doi.org/10.14743/apem2021.4.411

[22] Orso, V., Ziviani, R., Bacchiega, G., Bondani, G., Spagnolli, A. & Gamberini, L. (2022). Employee-centric innovation: Integrating participatory design and video-analysis to foster the transition to Industry 5.0. *Computers & Industrial Engineering*, *173*, 108661. https://doi.org/10.1016/j.cie.2022.108661

[23] Fraga-Lamas, P., Varela-Barbeito, J. & Fernández-Caramés, T. M. (2021). Next generation auto-identification and traceability technologies for industry 5.0: A methodology and practical use case for the shipbuilding industry. *Ieee Access*, *9*, 140700-140730. https://doi.org/10.1109/ACCESS.2021.3119775

[24] Qahtan, S., Alsattar, H., Zaidan, A., Pamucar, D. & Deveci, M. (2022). Integrated sustainable transportation modelling approaches for electronic passenger vehicle in the context of industry 5.0. *Journal of Innovation & Knowledge*, *7*(4), 100277. https://doi.org/10.1016/j.jik.2022.100277

[25] Nagy, L., Ruppert, T., Löcklin, A. & Abonyi, J. (2022). Hypergraph-based analysis and design of intelligent collaborative manufacturing space. *Journal of Manufacturing Systems*, *65*, 88-103. https://doi.org/10.1016/j.jmsy.2022.08.001

[26] Khan, W. U., Ihsan, A., Nguyen, T. N., Ali, Z. & Javed, M. A. (2022). NOMA-enabled backscatter communications for green transportation in automotive-industry 5.0. *IEEE Transactions on Industrial Informatics*, *18*(11), 7862-7874. https://doi.org/10.1109/TII.2022.3161029

[27] Richnák, P. & Fidlerová, H. (2022). Impact and Potential of Sustainable Development Goals in Dimension of the Technological Revolution Industry 4.0 within the Analysis of Industrial Enterprises. *Energies*, *15*(10), 3697. https://doi.org/10.3390/en15103697

[28] Senapati, T. & Yager, R. R. (2020). Fermatean fuzzy sets. *Journal of Ambient Intelligence and Humanized Computing*, *11*, 663-674. https://doi.org/10.1007/s12652-019-01377-0

[29] Chang, M.-H., Liou, J. J. & Lo, H.-W. (2019). A hybrid MCDM model for evaluating strategic alliance partners in the green biopharmaceutical industry. *Sustainability*, *11*(15), 4065. https://doi.org/10.3390/su11154065