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Analysis of Effective Components In Assessing Readiness For The Deployment of The Industry 5.0 In SME Using The DANP Technique

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ABSTRACT

The main objective of the present study is to identify and rank the factors affecting the establishment of Industry 5.0 in small and medium-sized industries. To achieve this goal, a combined fuzzy Delphi approach and the DANP multi-criteria decision-making method were utilized. In the initial stage, indicators were gathered through a literature review, and then expert opinions were collected and validated using the fuzzy Delphi method. Subsequently, key components were identified in five main dimensions: technology, social factors, infrastructure, industry characteristics, and innovation. These components and their relevant sub-dimensions were prioritized using the DANP method based on expert opinions. The study's key findings reveal that sub-dimensions such as "market demand" and "product and technology development" are of high importance, followed by "providing a skilled workforce" and "human resource development." Additionally, innovation components like "investment in startups" and "development of green products" play a significant role in driving the transition to Industry 5.0. The research underscores that successful implementation of Industry 5.0 necessitates a comprehensive focus on market-driven factors, human capital development, and digital infrastructure enhancement. By presenting an analytical framework, this study can serve as a valuable resource for managers in strategic planning and decision-making during the transition to Industry 5.0.

1. Introduction

Industrial transformations in the current era, amidst the digital revolution, have completely reshaped the global economy. With the advent of Industry 4.0, manufacturers have achieved unparalleled productivity through smartization, digitalization, and the integration of supply chains. However, the excessive focus on automation and efficiency has resulted in the neglect of crucial aspects that impact the success of implementation, such as human, ethical, and environmental considerations [1-2]. Therefore, a new concept known as Industry 5.0 has emerged in recent years, aiming to establish a balance between technology, humans, and the environment. Industry 5.0 is not

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simply a continuation of the fourth revolution, but a value-driven leap that highlights human-centeredness, sustainability, and resilience [3]. In essence, Industry 5.0 seeks to restore the creative, judgmental, and ethical role of humans in the production process, ensuring that smart technologies complement rather than replace humans [4]. In this model, artificial intelligence, collaborative robots, the Internet of Things, digital twins, and big data analytics serve as infrastructure, enhancing productivity while empowering human decision-making with increased accuracy [5]. The European Commission defines Industry 5.0 as a "human-centered, sustainable, and resilient industry" that prioritizes employee well-being, environmental protection, and intelligent growth [6]. Recent studies indicate that artificial intelligence is at the core of Industry 5.0, evolving from a mere analytical tool in Industry 4.0 to a cognitive partner for humans in Industry 5.0. The application of artificial intelligence in production and services enhances precision, reduces waste, predicts failures, and optimizes processes in real time [7]. Artificial intelligence, alongside machine learning and real-time decision-making, can shift production structures from static systems to self-learning and flexible systems [8]. Experts in the field emphasize that human-machine collaboration, workforce empowerment, and environmental sustainability are three essential components of Industry 5.0, achievable only through the intelligent use of technologies like artificial intelligence and the Internet of Things [9].

Despite all the aforementioned benefits of Industry 5.0, the successful deployment of this generation in industries faces fundamental challenges. Some of the most important challenges include: (1) lack of empirical and data-driven frameworks for assessing organizational readiness, (2) shortage of human resources specialized in artificial intelligence and smart technologies, and (3) lack of recognition of causal and network relationships between factors affecting Industry 5.0 success [10]. Most research in this field has remained conceptual, and quantitative studies modeling relationships between key Industry 5.0 factors still need development [11]. Identifying key factors, analyzing their relationships, and prioritizing them can significantly impact successful Industry 5.0 deployment in real-world settings and align with industry decision-making requirements. This study aims to comprehensively review literature on the subject, identify key components for successful Industry 5.0 deployment, evaluate and validate these components based on expert opinions, and assess their relationships and prioritization for deployment in small and medium-sized industries in Iran using the fuzzy Delphi technique. Finally, the latent relationships between these components and their relative prioritization will be evaluated using the DANP multi-criteria decision-making hybrid method.

2. Literature review

In this section, studies conducted in the field of evaluating the factors affecting the successful establishment of Industry 5.0 in the literature have been reviewed from two perspectives: identifying these factors and analyzing them.

2.1 Identifying Factors Affecting the Successful Establishment and Transformation of Industry 5.0

In Industry 5.0, efforts have been made to avoid excessive focus on automation and technology, which can lead to neglect of the role of humans, ethics, and sustainability. The key focus in this industry will be on creating a balance between technology, humans, and the environment. In other words, the human factor will be at the center of the production and decision-making system, and the technological factor will be considered as a tool for human empowerment [5, 12]. Industry 5.0 is a stage beyond digitalization that, in addition to productivity, also pays attention to the social, cultural, and environmental dimensions of development. This industrial generation seeks the convergence of smart technologies and human values to create a human-centered and resilient economy [13]. The results of the study show that Industry 5.0 can be considered a response to the shortcomings of Industry 4.0; the 4.0 industry has led to human inequalities and unsustainability in many industries, despite technological growth [14]. The results emphasize that the transformation and establishment of Industry 5.0 will only be successful when, in addition to technological investment, factors such as human capital and organizational culture are also considered [15]. Industry 5.0, as a revolutionary transformation in the world of industry, especially in the areas of creativity and decision-making, aims to promote artificial intelligence and sustainable development. This transformation is influenced by the synergy between humans and technology, which can lead to overcoming existing challenges in the industry and strengthening an effective role for humans in these processes. The results of the studies emphasize that Industry 5.0, by combining the concepts of human-centeredness and environmental sustainability, seeks a structural transformation that focuses not only on industrial production but also on promoting human-centered decision-making systems [15].

The results of studies conducted in the field of human resource management show that focusing on empowering human resources, especially through the use of new technologies and artificial intelligence, can have a significant impact on the process of industrial transformation [13]. In this regard, the use of artificial intelligence algorithms and self-learning systems plays an important role in supporting management decisions, which is especially evident in Industry 5.0. In a study focusing on the 5.0 generation university, Industry 5.0 is introduced as a platform for the synergy of education, research, and industry, in which learning and innovation occur bidirectionally between humans and intelligent systems. This concept shows that Industry 5.0 is not only related to the field of industry but also to the higher education system and human development [16]. Artificial intelligence is known as the driving force of Industry 5.0, which, with the ability to analyze big data, predict and make decisions in real time, can increase productivity and sustainability simultaneously [17]. The results of the studies emphasize that artificial intelligence and collaborative robots are among the most important enabling technologies in Industry 5.0, improving the quality of decision-making, reducing human error, and increasing innovation in organizations [18]. Studies show that Industry 5.0 has been described as the "era of cognitive collaboration between humans and machines," in which the interaction of humans and intelligent systems leads to increased productivity and employee satisfaction.

At the national level, the importance of utilizing artificial intelligence algorithms in recruiting, evaluating, and developing employees in Iranian industry was emphasized. It was noted that Industry 5.0, with its unique characteristics, can serve as a key tool in human resource development and workforce empowerment. The first step towards this direction involves cultural and ethical reforms related to new technologies, particularly artificial intelligence, which should be accompanied by ethical principles in decision-making and data analysis processes. These changes not only impact human resource management processes but also have the potential to drive organizational innovations and improvements in production structures [19]. The study highlights the necessity of creating multi-level decision-making processes for the effective implementation of Industry 5.0 in Iran. Industrial companies in Iran, especially those in emerging production sectors, continue to face challenges in adopting and optimizing new technologies. Iran is currently in a transitional phase towards Industry 5.0 and significant changes in management structures and technology infrastructure are required to enter this industry [20]. Research results underscore the importance of educational and research infrastructure for establishing Industry 5.0 in Iran. Industry 5.0 places a greater emphasis on artificial intelligence, Internet of Things, and blockchain technologies compared to other industries, leading to increased industrial demands towards Industry 5.0 [21-22]. Studies emphasize the need for advancements in production and service sectors, particularly in the 5th industry, with a holistic approach to integrating artificial intelligence between humans and machines.

Various industries and countries are striving to develop new generation technologies through processes like smart manufacturing. Researchers are working on software models to implement these technologies in industries and are analyzing existing trends to kick start new developments and industry entrepreneurship globally. Industrial changes are expected to enhance efficiency, reduce costs, and drive advancements in smart technologies and industrial processes, shaping the future of industrial progress. Global research highlights the enhancement of industrial practices and smart processes, as well as the transformation of small and medium-sized industries worldwide [23]. A systematic review of literature indicates that despite the significance of Industry 5.0 and its impact on organizational performance, few studies have explored the factors influencing its successful implementation. There is also a lack of integrated decision-making models that analyze the causal relationships between technological and human factors, with an excessive focus on technology at the expense of cultural and organizational dimensions.

2.2 Analysis of Factors Affecting the Successful Implementation of Industry 5.0

In the past decade, multi-criteria decision-making methods have been developed to analyze the complexities of Industry 5.0 using complex and multidimensional structures. Fuzzy Delphi and DEMATEL network analysis methods have been widely utilized to identify complex relationships and mutual dynamics between factors in Industry 5.0 [20]. Studies have highlighted that these methods can examine the relationships between technologies and social structures [11]. Recent research also emphasizes that combining fuzzy Delphi with network analysis can effectively analyze the interaction between technologies and humans in Industry 5.0 [10]. By using fuzzy Delphi and DEMATEL, they have analyzed the relationships between social marketing factors in Industry 5.0 and have shown that fuzzy approaches can reduce the uncertainty of human judgments and establish causal relationships between key indicators [16]. Research in the fields of sports and health has confirmed the effectiveness of fuzzy models in analyzing complex relationships. These findings underscore the importance of using fuzzy network models to understand the interactions between components of Industry 5.0 [24-25]. A combined approach of fuzzy Delphi and network analysis was used to identify human resource requirements in the fifth industrial revolution, and the findings show that "organizational learning, artificial intelligence ethics, and interdisciplinary skills" have the greatest weight among the success factors of Industry 5.0 [13]. Previous research emphasizes the importance of combining new technologies and empowering human resources for the success of Industry 5.0. This research has shown that technologies such as artificial intelligence and the Internet of Things play a key role in facilitating the processes of this industry. Additionally, the development of specialized human resources and management reforms are essential for the implementation of this industry. However, there are some gaps in existing research. One of the most important of these gaps is the lack of comprehensive frameworks for assessing the readiness of organizations to adopt Industry 5.0. Furthermore, many studies have focused on technological and economic dimensions, with less attention paid to social and cultural dimensions. Moreover, most of the research has been limited to specific industries, highlighting the need for a broader study at the national level and in the field of human resource management. The present study aims to address these gaps and conduct a more comprehensive analysis of the factors affecting the establishment of Industry 5.0 in Iran.

3. Problem Statement

With the increasing pace of technological and industrial developments in recent decades, the world is transitioning from the Fourth Industrial Revolution to the Fifth Industrial Revolution. Industry 5.0, which focuses on human-machine collaboration, environmental sustainability, and active participation of human resources in production processes, seeks to balance advanced technologies with social and human needs. Unlike the fourth generation, which mainly emphasized automation and digitalization, the fifth generation focuses on human-centeredness and better interaction between workers and robots to improve productivity and production quality, along with environmental sustainability and social welfare. This transformation faces particular challenges, especially in small and medium-sized industries, which face many problems due to resource, infrastructure, and skilled labor constraints. Small and medium-sized industries, which constitute an important part of the global economy, are unable to compete with larger industries in adopting these technologies due to financial constraints, lack of high-tech infrastructure, and shortage of skilled labor. In addition, the lack of complete familiarity with the benefits of Industry 5.0 technologies and the need for changes in organizational culture affect the speed of acceptance and deployment of these developments. For this reason, identifying key components for the successful deployment of Industry 5.0 technologies and determining implementation priorities for their adoption in medium and small industries is of particular importance. One of the effective methods for identifying and analyzing these components is the use of multi-criteria decision-making methods. In this research, the fuzzy Delphi method is used to collect expert opinions and analyze qualitative data, and the DANP method is used for network analysis and mutual relationships between components. These methods help to more accurately analyze and prioritize components in the deployment of Industry 5.0 in medium and small industries. In particular, the DANP method, by analyzing the network of causal relationships and interactions between different components, can provide a clear picture of the complex relationships of these components and offer practical solutions for implementing these technologies. Given the unique characteristics of Industry 5.0, in which new technologies are directly combined with human and social activities, human resource competence is one of the key components in this process. To successfully implement Industry 5.0 in medium and small industries, it is necessary for the human resource to continuously receive specialized training and digital empowerment. Additionally, proper management of cultural and organizational changes also plays a fundamental role in the acceptance of these technologies. Especially in medium and small industries, where resistance to change is more likely, there is a need for appropriate educational and management planning to strengthen human resource capabilities. For this research, multi-criteria decision-making methods such as the Fuzzy Delphi method and DANP will be used to identify and prioritize the components and indicators that affect the deployment of Industry 5.0 in small and medium-sized industries. The results of this research can help managers of small and medium-sized industries to facilitate the process of deploying Industry 5.0 in their organizations by prioritizing components and determining implementation strategies to exploit its benefits. This research focuses on small and medium-sized industries in developing countries, and small and medium-sized industries that are willing to implement 5.0 technologies in their production processes in Iran from 2023 to 2025 have been selected as the study case. Finally, this research will answer the research question: "What are the key factors affecting the readiness to deploy Industry 5.0 in small and medium-sized industries, and how their relative importance can be determined?" This research can serve as a strategic guide for small and medium-sized industries to effectively implement digital and industrial transformations in their organizations, improving productivity and quality while simultaneously promoting environmental sustainability and social well-being.

4. Analysis Method

Figure 1 presents the general steps of the analysis based on the Fuzzy Delphi and DANP methods.

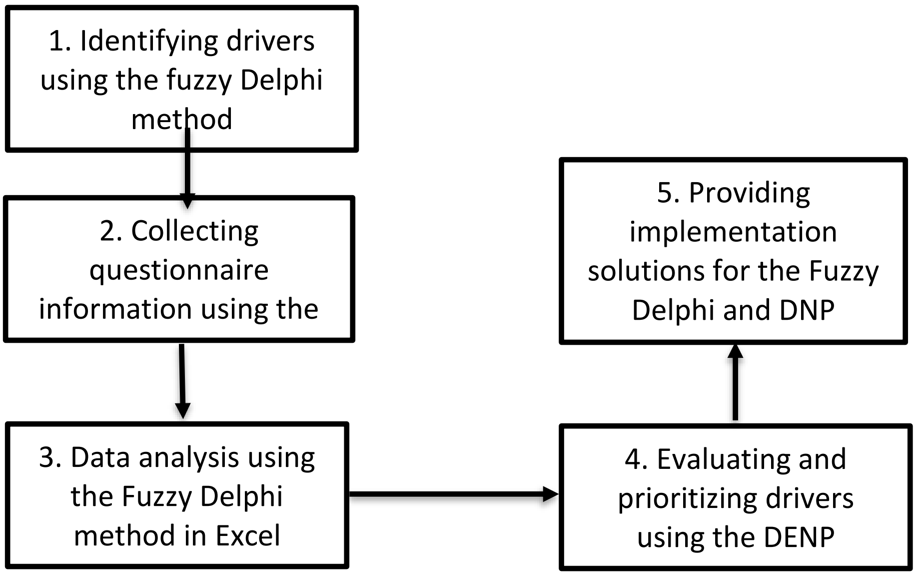

Fig. 1. Overal steps of the applied Analysis method in this study

Step 1: The first step involved defining drivers as the primary catalysts for transformation and essential elements for implementing changes in industries associated with Industry 5.0. Due to limited resources and infrastructure in medium and small industries, it is crucial to accurately identify these key factors. This phase resulted in the extraction of 5 main drivers (dimensions) and 21 related sub-criteria (components), forming the initial structural model of the research. These drivers encompassed technology, social aspects, infrastructure, industry innovation, and research and development (Table 1).

Table 1
Drivers and sub-criteria

Classification of drivers	Technology	Artificial intelligence Internet of things Blockchain Robotics
	Social	Awareness and Education Culture Change in supply of the force Specialist Resistance to Change
	Infrastrucure	Communications and Digital Infrastructure Physical Infrastructure Laws Sustainability and resource management
	Industry	Market demand Product and technology development Human Resources Developments
	Research & development	Research and development of new technologies Investing in startups and open innovation Research into new markets and consumer needs Developing sustainable and green products

Step 2: In this step, the questionnaire was distributed among 8 key experts and specialists in the field of industry and technology. The questions in the questionnaire were designed to capture the experts' opinions on the importance and priority of the drivers using fuzzy linguistic scales (such as low, medium, high, and very high). These linguistic scales were then transformed into triangular fuzzy

numbers to accurately represent the uncertainty and subjective differences among the experts' opinions in the data. Through the fuzzy Delphi technique, the individual opinions of the 8 experts (Table 2) were amalgamated into a consensus triangular fuzzy number for each component (Table 3).

Table 2
General information of experts

Num.	Field of work	Specialization	Length of work experience	Education level
1	Smart manufacturing systems in small and medium-sized industries	Industrial Management and Digital Transformation	15	PhD
2	Digital supply chain in small and medium-sized industries	Supply Chain Management	18	PhD
3	New production technologies	Industrial Automation	12	PhD
4	Innovation and technology management in small industries	Technology Management	10	PhD
5	Multi-criteria modeling and decision-making in industrial systems	MCDM and Decision Support Systems	14	PhD
6	Implementation of digital transformation technologies in manufacturing industries	Industrial Productivity and Consulting	16	PhD
7	Sustainability, human-centeredness and Industry 5.0 in manufacturing	Industrial Sustainable Development	9	PhD
8	Operations planning and control in small and medium-sized industries	Operations Management	11	PhD

Table 3
Triangular fuzzy numbers of the 5-point Likert scale

Verbal Variable		Triangular Fuzzy Numbers
Very Low	VL	(0, 0, 0.25)
Low	L	(0, 0.25, 0.5)
Medium	M	(0.25, 0.5, 0.75)
High	H	(0.5, 0.75, 1)
Very High	VH	(0.75, 1, 1)

Step 3: In this step, the aggregated data from the second step, which were in the form of triangular fuzzy numbers expressing the consensus of the opinions of 8 experts, were entered into the Excel software environment to perform the defuzzification process on them (Table 4). The main goal of defuzzification is to convert the qualitative and ambiguous fuzzy data into a definite and quantitatively interpretable value. After defuzzification, the definite values for each of the 21 sub-criteria were used to determine the acceptance boundary and final validation. By defining a specific threshold limit (for example, a value of 3.5 or 4 in the range of 1 to 5), only the components whose defuzzified average was higher than this threshold were identified and verified as key and valid components for the deployment of Industry 5.0 in medium and small industries. Data analysis at this stage ensures final clarification of priorities and validation of the structure of the 5 drivers and 21 sub-criteria, and confirms the accuracy of the data for entry into the causal modeling phase. The goal

of this step is to accurately process and ensure consensus and sufficiency of the data before running more complex models.

Table 4
The results obtained from the fuzzy Delphi method

Threshold: 0.7				Fuzzy average		
ID	Criteria	Sub-criteria	Defuzzified	U	M	L
1	technology	Artificial intelligence	0.86	0.97	0.94	0.69
2		Internet of Things	0.72	0.91	0.75	0.50
3		Blockchain	0.76	0.97	0.78	0.53
4		Robotics	0.80	0.97	0.84	0.59
5		Cloud computing	0.74	0.91	0.78	0.53
6	Social	Awarness and education	0.73	0.94	0.75	0.50
7		Change culture	0.79	0.94	0.84	0.59
8		Provision of expert labor	0.77	0.94	0.81	0.56
9		Resistance to change	0.88	1.00	0.94	0.69
10	Infrastructure	Digital infrastructure	0.85	1.00	0.91	0.66
11		Physical infrastructure	0.75	0.94	0.78	0.53
12		Laws	0.81	1.00	0.84	0.59
13		Sustainability and resource management	0.72	0.91	0.75	0.50
14		Expert labor	0.71	0.94	0.72	0.47
15	Industry	Market demand	0.74	0.91	0.78	0.53
16		Product and technology development	0.80	0.97	0.84	0.59
17		Human resource developments	0.84	0.97	0.91	0.66
18	Innovation and R&D	Research and development of new technologies	0.83	1.00	0.88	0.63
19		Investing in startups and open innovation	0.73	0.94	0.75	0.50
20		Research in new markets and consumer needs	0.82	0.97	0.88	0.63
21		Development of sustainable and green products	0.85	1.00	0.91	0.66

The implementation steps of the fuzzy Delphi method are as follows:

Formation of Fuzzy Opinion Matrices: At this stage, the linguistic responses of all 8 experts for each of the 21 sub-criteria, based on the determined 5-grade linguistic scale, were converted into the equivalent of triangular fuzzy numbers. Consequently, a fuzzy number is generated for each sub-criterion and each expert.

Calculation of The Consensus Fuzzy Average: To achieve a single consensus and minimize the impact of individual bias, the individual triangular fuzzy numbers of the experts are combined using the fuzzy aggregation method to derive the consensus fuzzy number for each sub-criterion (Averaging relation of fuzzy Delphi method). Equation (1) is utilized in the fuzzy Delphi method to aggregate the individual judgments of experts and calculate the group fuzzy average for each sub-criterion.

$(u, m, j) = \tilde{A}$

$$k\sum_{k=1}^{u}\frac{1}{n} = \bar{u}\,, k^{m}\sum_{k=1}^{n}\frac{1}{n} = \bar{m}\,, k^{J}\sum_{k=1}^{n}\frac{1}{n} = \bar{J} \tag{1}$$

De-fuzzification and extraction of definite values: In this step, the consensus fuzzy number is converted into a definitive value using the surface center method or fuzzy weighted average, allowing it to be used in quantitative analysis. The resulting value represents the weight or absolute importance of each sub-criterion, reflecting the consensus of experts' opinions.

Verification and final refinement of components: Finally, the obtained cut-off values were compared with the predetermined threshold limit of 0.7. A threshold of 0.7 is defined to ensure the content validity and necessity of the component in the model, representing the minimum level of acceptance for each sub-criterion. If the value of a component exceeds the threshold limit, it is considered a valid and key factor, progressing to the next stage of DANP modeling research. This process ensures the structural accuracy of the research model.

Step 4. This step marks the transition to structural modeling in the DANP method, aiming to model and quantify the mutual cause-and-effect relationships between 21 key research sub-criteria. The calculation process in this step was professionally coded and executed in the MATLAB software environment. The implementation steps are as follows:

DIMATEL's process begins with the utilization of a specific direct relationship matrix. This 21 x 21 matrix reflects the consensus of experts' opinions regarding the extent of direct influence of each sub-criterion on the others, which was determined after the final de-fuzzification in the third step. Within the matrix, the elements along the main diagonal are considered to be zero (representing the direct relationship matrix of the DANP method). The primary direct effects matrix illustrates the strength and direction of the direct influence between the sub-criteria based on expert opinions and serves as the primary input for calculating causal relationships and indirect effects in the DANP method.

$$\mathrm{A} = \begin{vmatrix} a_{11} & a_{1j} & a_{1n} \\ a_{i1} & a_{ij} & a_{in} \\ a_{n1} & a_{nj} & a_{nn} \end{vmatrix} \tag{2}$$

Direct Matrix Normalization: In order to prepare the matrix for chain calculations, a normalization operation was performed. The code for this operation was written in MATLAB, which involved calculating the normalization coefficient and then applying it to the entire matrix (DANP matrix normalization relation). In this relation, Equation (3) calculates the largest row and column sum of the matrix of direct effects, and then selects the minimum value of their inverse as the normalization coefficient to prevent calculation divergence [26].

$$S = min\left[\frac{1}{max\sum_{j=1}^{n}|a_{ij}|}\frac{1}{max\sum_{i=1}^{n}|a_{ij}|}\right] \tag{3}$$

Calculation of the Total Relationship Matrix: The most crucial aspect of this step is calculating the matrix T of total relationships. This matrix is at the core of the DANP method, allowing for the comprehensive calculation of direct effects, as well as all indirect and chain effects between sub-criteria. This process is carried out in the MATLAB environment, where the unit matrix is 21x21. It involves matrix inversion and multiplication, which are essential for the total matrix of the DANP method. Equation (4) demonstrates that as the power of the normalized matrix increases, the resulting matrix approaches the zero matrix. This characteristic is vital for calculation stability and enables the calculation of total effects in the DANP method, preventing the divergence of influence chains between sub-criteria.

$$lim\, m \to \infty x^{m} = [0]n * n \tag{4}$$

The output of this process is the T matrix, which quantitatively depicts the final causal and consequential structural model of the sub-criteria. This matrix not only illustrates the mutual relationships but also serves as the total influence matrix, the main and vital input for calculating the final DANP weights (in step 5). This causal structure enables a more detailed analysis of relationships and prioritization based on the network structure (normalized matrix relationship). Equation (5) represents the calculation of the total effects matrix, which is obtained through the sum of direct and indirect effects resulting from the successive powers of the normalized matrix. Using this relationship allows for a comprehensive analysis of the causal relationships between the sub-criteria and identifying the real role of each factor in the decision-making network structure [26].

$$T = x + x^2 + \cdots + x^h = x = (I - x)^{-1} \tag{5}$$

Step 5: In this final phase of the research, the quantitative analysis takes place. The goal is to calculate the final weights of the 21 sub-criteria by considering the network's cause and effect relationships. This process involves combining the total relationship matrix T, obtained from DANP (step 4), with the Analytical Network Process (ANP) structure. Each step of this process has been executed sequentially, utilizing specialized coding within the MATLAB environment.

Calculation of The Weight Matrix For The Main Criteria: In order to model the dependency relationships between the 5 main drivers (clusters), the total relationship matrix is first separated based on the main dimensions to calculate the total impact matrix between the criteria "TC". Each element of the matrix STC represents the total effect of one drive sub-criteria on another drive sub-criteria. Next, the STC matrix is converted to the weight matrix for the main criteria (WB) through row normalization. This 5x5 matrix determines the relative weights of the influence of each driver on the other drivers as external weights.

Compilation of the unweighted superfinal matrix: In this step, the unweighted superfinal matrix is compiled to extract the intra-cluster influence weights of the sub-criteria. The total effects matrix is divided into sub-blocks corresponding to each cluster of sub-criteria. Each block illustrates the influence of the sub-criteria within a cluster on each other. These blocks are then individually subjected to the column normalization process to ensure that the sum of the elements in each column is equal to one. This normalization allows for a comparison of the relative intensity of the effects within each cluster. The output of this step is the unweighted superfinal matrix, which displays the internal dependency weights of the sub-criteria without considering the weight of the clusters. This matrix serves as the foundation for the formation of the weighted superfinal matrix in the subsequent steps of the DANP method. Equation (6) structures the unweighted superfinal matrix by combining the normalized blocks of influences, showing the intra-clustering of sub-criteria and reflecting the internal dependence of sub-criteria without applying cluster weights [27].

$$\mathbf{Tc} = \begin{array}{ll} D_1 & \begin{array}{c} C_{11} \\ C_{12} \\ C_{1m1} \end{array} \\ D_i & \begin{array}{c} C_{i1} \\ C_{i2} \\ C_{imi} \end{array} \\ D_n & \begin{array}{c} C_{n1} \\ C_{n2} \\ C_{\ nmn} \end{array} \end{array} \begin{vmatrix} T_C^{11} & T_C^{1j} & T_C^{1n} \\ T_C^{i1} & T_C^{ij} & T_C^{in} \\ T_C^{n1} & T_C^{nj} & T_C^{nn} \end{vmatrix} \tag{6}$$

Calculation of Superfinal Matrix: This 21x21 matrix represents the entire structure of the network. The weighted superfinal matrix of the supermatrix is calculated by applying the weights of the drivers to the corresponding blocks in the matrix. This process combines the internal influence weights with the external relative importance of the drivers to create a comprehensive model of the network's component importance (relationship of the superfinal matrix of the DANP method). Equation (7) illustrates the process of forming the weighted superfinal matrix in the DANP method. In the first step, the total effects matrix, which indicates the direct and indirect effects between the sub-criteria, is based on the clusters corresponding to the sub-blocks of separation. Each block demonstrates the intensity of the sub-criteria of one cluster on the sub-criteria of another cluster.

$$\boldsymbol{T_C^a} = \begin{vmatrix} T_C^{a11} & T_C^{a1j} & T_C^{a1n} \\ T_C^{ai1} & T_C^{aij} & T_C^{ain} \\ T_C^{an1} & T_C^{anj} & T_C^{ann} \end{vmatrix} \tag{7}$$

Next, for each sub-block, the internal influence weights of the sub-criteria are calculated using the obtained values. The sum of the elements of each row or column (depending on the block structure) is aggregated in order to extract the relative influence vectors (Relation 8). This stage allows us to determine the relative contribution of each sub-criterion in intra-cluster and inter-cluster interactions.

$$\boldsymbol{T_C^{12}} = \begin{array}{c} c_1 \\ c_j \\ c_n \end{array} \begin{vmatrix} T_C^{a11} & T_C^{a1j} & T_C^{a1n} \\ T_C^{ai1} & T_C^{aij} & T_C^{ain} \\ T_C^{an1} & T_C^{anj} & T_C^{ann} \end{vmatrix} \rightarrow t_1^{12} = \sum_{j=1}^{m_2} t_{1j}^{12} \tag{8}$$

Then, the resulting blocks are combined with the weights of the corresponding clusters so that the effect of the relative importance of the clusters is included in the network structure (Relation 9). The result of this process is the formation of the weighted super final matrix, in which both the internal dependencies of the sub-criteria and the relative importance of the upstream clusters are considered simultaneously. The weighted super final matrix reflects the complete structure of the decision network and is used as the main input to calculate the super final matrix (final limit) and derive the stable final weights of the sub criteria (Relation 10). These weights are the basis of the final ranking and analysis of the importance of the factors in the framework of the DANP method (Relation 11) [27].

$$\boldsymbol{T_C^{12}} = \begin{array}{c} c_1 \\ c_j \\ c_n \end{array} \begin{vmatrix} T_C^{a11} & T_C^{a1j} & T_C^{a1n} \\ T_C^{ai1} & T_C^{aij} & T_C^{ain} \\ T_C^{an1} & T_C^{anj} & T_C^{ann} \end{vmatrix} \rightarrow t_1^{12} = \sum_{j=1}^{m_2} t_{ij}^{12} \tag{9}$$

$$\boldsymbol{T_C^{12}} = \begin{array}{c} c_1 \\ c_j \\ c_n \end{array} \begin{vmatrix} T_C^{a11} & T_C^{a1j} & T_C^{a1n} \\ T_C^{ai1} & T_C^{aij} & T_C^{ain} \\ T_C^{an1} & T_C^{anj} & T_C^{ann} \end{vmatrix} \rightarrow t_{m_1}^{12} = \sum_{j=1}^{m_2} t_{mij}^{12} \tag{10}$$

$$\mathbf{Tc} = \begin{array}{cc} & \\ D_1 & \begin{array}{c} C_{11} \\ C_{12} \\ C_{1m1} \end{array} \\ D_i & \begin{array}{c} C_{i1} \\ C_{i2} \\ C_{imi} \end{array} \\ D_n & \begin{array}{c} C_{n1} \\ C_{n2} \\ C_{nmn} \end{array} \end{array} \begin{vmatrix} W_{11} & W_{1j} & W_{1n} \\ W_{i1} & W_{ij} & W_{in} \\ W_{n1} & W_{nj} & W_{nn} \end{vmatrix} \tag{11}$$

Calculation of Final Weight and Ranking: In order to determine stable final weights, the normalized hyper weighting matrix needs to be raised to repeated powers until convergence is reached. Using MATLAB coding, the normalized super weighting matrix was raised to the power of K=200 to achieve the final super weighting matrix. The final weights are calculated by extracting the values from one of the columns of the extreme final weighting matrix (in cases of convergence, all columns will be identical) and then normalizing these values. These values represent the final and comprehensive weights of the 21 sub-criteria that determine the overall importance of each component, considering both direct and indirect effects within the network. These weights were directly applied to the final ranking and prioritization of factors influencing the establishment of the 5.0 generation industry in medium and small industries (final weight relationship and ranking of the DANP method). To obtain stable final weights for the sub-criteria, the weighted super final matrix is normalized and raised to successive powers until convergence is reached (Relation 12). By raising the super final matrix to the power of K=200, a finite final matrix is obtained. In the convergence state, the values of the columns in this matrix become identical, indicating the stability of the network structure and the independence of results from the initial values (Relation 13).

$$T_D = \begin{vmatrix} t_D^{11} & t_D^{1j} & t_D^{1n} \\ t_D^{i1} & t_D^{ij} & t_D^{in} \\ t_D^{n1} & t_D^{nj} & t_D^{nn} \end{vmatrix} \tag{12}$$

$$T_D^a = \begin{vmatrix} t_{11}/t_1 & t_{1j}/t_1 & t_{1n}/t_1 \\ t_{i1}/t_i & t_{ij}/t_i & t_{in}/t_i \\ t_{n1}/t_n & t_j/t_n & t_{nn}/t_n \end{vmatrix} \tag{13}$$

After obtaining the limit super finite matrix, the final weight of each sub criterion is determined by extracting the values of one of the columns of this matrix and performing the final normalization (Relation 14). These weights show the relative importance of each sub-criterion by considering all the direct and indirect effects between network elements and are the basis of the final ranking of the sub-criteria. The normalization performed on the weighted super finite matrix provides a necessary condition for the stability of numerical calculations and prevents the divergence of the influence chain between sub criteria. Therefore, the resulting weighted matrix reflects the complete structure of network dependencies and enables the reliable calculation of final weights within the framework of the DANP method [27].

$$\boldsymbol{w^a} = \boldsymbol{T_D^a} w = \begin{vmatrix} t_D^{a11}/W^{11} & t_D^{a1j}/W^{i1} & t_D^{a1n}/W^{n1} \\ t_D^{ai1}/W^{1J} & t_D^{aij}/W^{ij} & t_D^{ain}/W^{nj} \\ t_D^{an1}/W^{1n} & t_D^{anj}/W^{in} & t_D^{ann}/W^{nn} \end{vmatrix} \tag{14}$$

Providing Implementation Solutions: Based on the precise and quantitative ranking of the final DANP weights, implementation and strategic solutions for Industry 5.0 are formulated. The results indicate that the focus should be on components with the highest weight, such as "market demand" and "product and technology development," to optimally allocate limited resources in small and medium-sized industries. These solutions are directly developed from the results of the structural analyses and priorities identified through the DANP method. Step 6: In this section, the results from the DANP ranking and causal analysis are combined to formulate managerial and strategic implications of the research. This summary not only evaluates the positive effects of the implementation solutions developed in Step 5 on the performance of target industries but also identifies challenges and problems in implementing this industry based on causal relationships. This step will conclude the research and, by providing analytical insights, form the basis for management and strategic decisions for the successful transition to Industry 5.0 in medium and small industries.

5. Results

In the present study, a comprehensive understanding of the factors affecting the readiness of Industry 5.0 in small and medium-sized industries was sought using a combined analytical framework based on expert judgment and network analysis. The analysis process was designed to systematically consider the complex interactions and causal relationships between criteria and sub-criteria while reducing uncertainties arising from human judgment. First, a set of potential sub-criteria was identified through a systematic literature review and exploratory interviews with industry and technology experts. These sub-criteria represented various technical, human, organizational, technological, and environmental dimensions related to the establishment of Industry 5.0. To validate and refine this initial set, the Fuzzy Delphi method was utilized to achieve relative consensus among the experts. The experts' judgments were expressed using five-point verbal scales, which were converted into corresponding triangular fuzzy numbers to account for uncertainty and ambiguity in human assessments. Next, the experts' opinions were aggregated in fuzzy form, and the group fuzzy mean was calculated for each sub-criterion. Subsequently, the aggregated fuzzy values underwent defuzzification to obtain definite values for decision-making. Sub-criteria with less importance than the specified threshold were eliminated to increase the focus and accuracy of the analysis. After finalizing the set of sub-criteria, the interrelationships and causal effects between criteria and sub-criteria were examined using network analysis. A direct effects matrix was formed to determine the degree of influence of each sub-criterion on others based on expert judgments. This matrix was normalized to make values comparable and prevent scale dominance. The total effects matrix considered all direct and indirect effects between sub-criteria, providing a comprehensive picture of influence intensity and degree within the decision-making network. Sub-criteria were then grouped based on thematic clusters corresponding to main criteria, and relative weights were calculated to determine the importance and relationships between them. This process enabled simultaneous analysis of intra- and inter-cluster relationships, completing the decision-making network structure. A normalized overweighting matrix was formed by combining results from intra- and inter-cluster relationships, representing the flow of influence between all criteria and sub-criteria. To extract stable final weights, the matrix was raised to successive powers to minimize changes and achieve convergence. After convergence, a marginal (final) overweighting matrix was obtained, indicating the final weight of each sub-criterion. These weights, after normalization, were considered final weights for the sub-criteria. Based on the final weights obtained (Table 5), the sub-criteria were ranked, indicating the relative importance of various factors in the readiness of small and medium-sized industries for Industry 5.0 deployment. This ranking can provide a scientific basis for prioritizing strategic actions, allocating resources, and formulating support policies in this area. The results highlight the importance of understanding network interactions between factors in explaining the complexities of Industry 5.0 deployment. The approach used in this research can serve as a suitable model for analyzing similar issues in other industrial areas.

Table 5
Evaluation results of criteria and sub-criteria

Criteria	Sub-criteria	Weight	Rank
Technology	Artificial intelligence	0.0400	15
	Internet of Things	0.0395	16
	Blockchain	0.0381	17
	Robotics	0.0377	18
	Cloud computing	0.0447	12
Social	Awareness and education	0.0373	19
	Change culture	0.0457	10
	Provision of expert labor	0.0671	3
	Resistance to change	0.0499	7
Infrastructure	Digital infrastructure	0.0459	8
	Physical infrastructure	0.0434	13
	Laws	0.0407	14
	Sustainability and resource management	0.0359	20
	Expert labor	0.0341	21
Industry	Market demand	0.0704	1
	Product and technology development	0.0704	2
	Human resource developments	0.0592	4
Innovation and R&D	Research and development of new technologies	0.0458	9
	Investing in startups and open innovation	0.0599	5
	Research in new markets and consumer needs	0.0457	11
	Development of sustainable and green products	0.0526	6

6. Conclusion

The results of this study show that the fifth generation industry is not simply a continuation of the fourth generation industry, but rather a new stage of industrial maturity where technology, humans, and the environment interact in a balanced way. The primary objective of this industrial generation is to combine human cognitive abilities and machine computational power to establish a production and management system that prioritizes sustainability, innovation, and social welfare alongside productivity. The findings from the combined Delphi Fuzzy and Denp models indicate that successful transition to the fifth generation industry necessitates a comprehensive approach that takes into account technological, human, infrastructure, and management factors simultaneously. Obtained results of this study are approved by previous studies [28-34]. The analyses reveal that "market demand" and "technology and product development" are of utmost importance as they directly influence the organization's innovation and competitiveness. Additionally, "Provision of specialized human resources" and "human resource transformations" are identified as crucial drivers of transformation that are essential for adapting to the requirements of the Fifth Industrial Revolution. The study highlights that deploying the 5.0 generation industry in small and medium-sized industries requires a holistic view that considers the interaction between technological, human, organizational, and environmental factors. Unlike previous industrial transformation models that focused on automation and technological productivity, this study emphasizes the significance of synergy between human capabilities, smart technologies, and sustainability requirements in the success of the deployment process. It is recommended that managers of small and medium-sized industries develop phased transition plans to the 5.0 generation industry by prioritizing key factors. Investing in digital technologies, enhancing human skills, and strengthening management structures simultaneously can significantly enhance the effectiveness of the deployment process. Specialized training, redesigning decision-making processes, and fostering organizational innovation are suggested practical measures for achieving this. From an industrial policy perspective, the study suggests that the success of small and medium-sized industries in adopting the 5.0 generation industry relies on the active involvement of policy-making institutions in creating supportive infrastructure. Providing financial incentives, developing shared digital infrastructure, and supporting training programs can help bridge the technological gap and facilitate the transition. While challenges such as limited financial resources, lack of specialized human resources, organizational resistance, and immature technological infrastructure may arise during the implementation of the 5.0 generation industry in small and medium-sized industries, a realistic and gradual approach tailored to each industry's local conditions is essential to mitigate risks and maximize effectiveness. In conclusion, this study offers an analytical framework for understanding the readiness of small and medium-sized industries for the 5.0 generation industry, serving as a scientific basis for decision-making by managers, policymakers, and industrial planners. By emphasizing the network interaction of factors and focusing on human, technological, and sustainability dimensions, this research sets the stage for balanced and human-centered industrial development. Overall, the fifth generation industry represents a stage of industrial evolution where human values, technological innovation, and environmental sustainability converge in an intelligent decision-making system. The findings of this research can inform industrial policies, human capital development, and digital transformation roadmaps across various industries, leading the way towards a sustainable, resilient, and human-centered industry.

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Data Availability Statement
The data that support the findings of this study are available from the corresponding author upon reasonable request.

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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