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Enhancing Decision-Making Processes in the Complex Landscape of the Taiwanese Electronics Manufacturing Industry through a Fuzzy MCDM Approach

Wen-Chin Chen ¹, An-Xuan Ngo ¹  and Hui-Pin Chang ^{2,*}

¹ Ph.D Program of Management, Chung Hua University, Hsinchu 30012, Taiwan; wenchin@chu.edu.tw (W.-C.C.); ngoxuanan211@gmail.com (A.-X.N.)

² School of Innovation and Entrepreneurship, Shaoguan University, Shaoguan 512005, China

* Correspondence: huipinchang@outlook.com

Abstract: This research proposes a hybrid multi-criteria decision-making (MCDM) framework for workforce recruitment in Taiwan's electronics manufacturing companies, an area with limited research. First, a comprehensive review of existing literature and interviews with industry experts were conducted to compile a list of decision-making criteria and sub-criteria relevant to workforce selection in Taiwan's electronics industry. The Fuzzy Delphi Method (FDM) was then applied to identify and retain the most critical criteria while eliminating the less important ones. Next, Interpretive Structural Modelling (ISM) was used to calculate the interdependencies among the identified factors. Finally, based on these relationships, the Fuzzy Analytic Network Process (FANP) was employed to calculate the relative importance weights of the criteria and sub-criteria. These weights were then used to rank the criteria, identifying the most important ones and aiding in decision-making. The findings indicate that the proposed method provides a structured and assessable model for making informed decisions in workforce recruitment, particularly in the challenging environment of Taiwan's electronics manufacturing industry, which faces a shortage of skilled labor. The research presents three primary contributions: the development of a systematic criteria selection technique using FDM, the establishment of consistent criteria relations for decision-makers using ISM, and the proposal of an application model employing the FANP method to identify and rank appropriate criteria for hiring new employees. The study highlights work attitude, adaptability to the environment, and work ability as major criteria. It also emphasizes the importance of discipline compliance, a positive attitude, and adherence to health and safety protocols as the top sub-criteria for workforce selection.

Keywords: decision process; MCDM; FDM; ISM; FANP

MSC: 03B52; 90B50; 90B70; 62J15



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1. Introduction

Taiwan's manufacturing industry faces a workforce shortage due to the younger generation's reluctance to enter the field and an aging population with declining birth rates. This situation has increased a significant gap between the demand for manufacturing workers and the available supply. According to the 2024 global talent shortage report by Manpower Group, 73% of employers in Taiwan report recruitment difficulties. The Taiwan Ministry of the Interior's data show birth rates dropping from 305,312 in 2000 to 135,571 in 2023, exacerbating the issue. Taiwan has emerged as one of the most rapidly aging societies globally, significantly impacting its economy and labor market [1]. Various studies explore the negative impacts of population aging and low fertility rates on productivity and economic development [2–5]. According to the Workforce Development Agency, Ministry of Labor, Taiwanese companies struggle to recruit local talent and hire

workers from Indonesia, the Philippines, Thailand, and Vietnam to address the effects of an aging population and reduce wage expenses in the electronics manufacturing industry [6]. Recruiting personnel of different nationalities involves distinct approaches that vary in recruitment schedules and cultural tendencies [7]. Building a diverse, high-performance workforce in Taiwan's electronics manufacturing requires selecting individuals with training potential and employing a methodical approach, including evaluation, selection, and development [8]. Selecting a recruitment method that takes longer during urgent manpower needs can result in inadequate manpower when capacity is full, posing challenges for production and human resource department heads [9]. Previous studies have shown that an efficient workforce significantly enhances firm productivity in Taiwan, contributing to overall performance, playing a crucial role in sustainable national development, and boosting national competitiveness [10–14]. Human Resources are crucial in recruiting and selecting manufacturing talent, using selective staffing to reduce turnover, boost productivity, minimize costs, maximize profitability, and ensure smooth production by optimally allocating labor [15,16]. Personnel selection is crucial in human resources management for identifying qualified candidates, emphasizing a systematic hiring process to minimize turnover and enhance profitability [17–22]. Traditional methods like Grade Point Averages (GPAs), tests, essays, and interviews are no longer sufficient for identifying manufacturing talent, and while written and oral exams are crucial, they are insufficient alone for hiring the needed personnel [23,24]. Only a minority of these studies make use of MCDM techniques [25]. To recruit individuals for electronics fabrication facilities, new evaluation methods should integrate technology-driven survey methodologies and data analytics. Specifying and weighting assessment criteria, combining subjective judgment with objective analysis, is crucial for effective selection, as tools lacking specific criteria and weights can lead to unsatisfactory selections [26]. This study proposes a hybrid MCDM model to determine the most critical criteria for workforce selection in Taiwan's electronics manufacturing industry.

Defining selection criteria is crucial in workforce selection, yet many studies lack a systematic approach, focusing more on numerical examples than on establishing a proper method. This oversight could lead to inaccuracies in the final decision-making process [27–30]. Academia has identified numerous essential competency criteria for selecting a workforce [31,32]. However, defining a definitive framework for workforce selection decision-making is challenging, if not impossible, due to the dispersion of criteria and the uncertainty they present for organizations [33,34]. Managers can benefit from prioritizing criteria and sub-criteria to focus on the most crucial indicators, especially when resources are limited [35]. The literature reveals a need for further studies on criteria selection in workforce selection problems, particularly for improving accuracy and reevaluating priorities, as traditional measurement methods often fall short in assessing critical criteria [36]. Therefore, there is a need to incorporate a systematic method for selecting criteria [37]. The evaluation of job candidates is complex due to the difficulty of assessing their skills, but using fuzzy theory can improve assessment efficiency and reduce subjective judgment by translating verbal expressions into numerical ones through fuzzy linguistic models [38,39]. Moreover, studies often use the FDM to prioritize key criteria when examining the relative importance of selecting the right ones [40]. However, only a few studies have employed the FDM to identify the critical criteria for the workforce selection process [34]. This study focuses on the workforce selection process in Taiwan's electronics manufacturing industry. It uses the Delphi method to select suitable candidates based on conflicting criteria and employs fuzzy logic to enhance reliability. The first contribution of this study is a systematic criteria selection technique developed through literature review and expert interviews. The FDM is then used to retain the most critical criteria and eliminate less important ones.

Furthermore, MCDM techniques have been developed to help decision-makers make well-informed choices by considering multiple decision criteria [41]. However, current MCDM techniques often assume that criteria are independent, overlooking the significant impact that relationships among criteria can have on final decisions [42]. Recognizing these

interrelationships is crucial for an efficient workforce selection process. Despite this importance, there is a scarcity of studies investigating these relationships, and many existing methods neglect these interdependencies [43–45]. ISM establishes relationships among decision system elements, creating a structured knowledge base that simplifies understanding by identifying and condensing relationships among specific variables defining a problem or issue [46]. Many studies have adapted ISM for use in strategic decision-making groups, highlighting the interconnections between criteria and their hierarchical levels [47]. Few studies examine the interdependencies between criteria in workforce selection. Many current methods assume independence among factors despite the reality that any factor could be related to or dependent on another [28]. In this regard, the next contribution of the study is to establish and measure various relationships among decision criteria for workforce selection. This will aid decision-makers in Taiwan's electronics manufacturing industry by providing consistent criteria relations through the ISM approach.

MCDM systems are essential for simplifying the intricate process of determining candidate rankings and criteria weights in employer decision-making [38]. Various MCDM techniques, such as the Analytic Hierarchy Process (AHP), the Analytic Network Process (ANP), and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), are applied in workforce selection. Studies often utilize AHP or fuzzy AHP to prioritize criteria [48]. The AHP approach is commonly used to determine factor weights or relative importance, assuming independence among factors within the hierarchical structure. However, this assumption may overlook potential dependencies, which could contradict the underlying hypothesis of the AHP method [49]. The significance of factors lies not only in their individual weights but also in the weights derived from their mutual interactions [50]. Employing the ANP method, which considers interdependencies between factors, in the personnel selection model is expected to improve the objectivity of decisions [51]. Moreover, it is crucial to acknowledge that human judgment naturally aligns with fuzzy approaches, rendering fuzzy logic a suitable tool for comparisons [52]. This study proposes an application model that uses the FANP method, a type of MCDM approach, to identify the most suitable criteria for personnel recruitment in Taiwan's electronics manufacturing companies. It aims to assist the human resources department in selecting and prioritizing criteria based on calculated weights.

By addressing the severe shortage of skilled labor in the industry, this research provides strategic recommendations to managers and contributes to the field by combining the FDM, ISM, and FANP for personnel selection in Taiwan's electronics manufacturing industry. It involves selecting the most important criteria and sub-criteria from a large set. The research introduces a systematic criteria selection technique developed through a literature review and expert interviews. The FDM is used to retain critical criteria, while the ISM establishes relationships among decision criteria. The FANP method identifies and prioritizes the most suitable criteria based on calculated weights. The criteria and sub-criteria were created based on a comprehensive literature review and expert insights, ensuring high relevance to real-world challenges. Additionally, the research includes a comparative analysis with traditional workforce recruiting methods, showcasing the advantages and improvements of the proposed hybrid multi-criteria decision-making (MCDM) framework. This research proposes an approach applicable to similar industries and provides recommendations for human resource and manufacturing unit heads.

This paper is structured as follows: Section 2 provides an overview of various existing decision-making techniques, discusses their drawbacks and challenges, and identifies research gaps. Section 3 outlines the proposed methodology, which combines various Fuzzy MCDM methods to enhance the decision-making process. Section 4 presents the findings, Section 5 covers the discussion, and Section 6 provides the conclusion and recommendations for future research.

2. Literature Review

Given the profound impact a well-suited workforce can have on the future trajectory of the manufacturing industry, enterprises must carefully consider the pivotal factors influencing personnel selection to ensure sound decision-making. This study introduces an innovative model for evaluating labor force recruitment in Taiwan's manufacturing industry and integrates the FDM, ISM, and FANP. Designed specifically for Taiwan's electronics manufacturing industry, this model provides a systematic approach to enhance the human resource selection process.

2.1. FDM

Emerging in the 1960s as a response to limitations in conventional predictive methods like theoretical models, quantitative analyses, and trend extrapolation, the Delphi Method offered an innovative approach. However, challenges regarding ambiguity and uncertainty in survey questions and responses persisted [53]. In 1985, the introduction of fuzzy set theory to the Delphi Method led to the development of the FDM. Originally conceived by Dalkey and Helmer in 1963, the Delphi Method has been widely applied in research, emphasizing the superiority of collective judgments over individual ones. It typically involves multiple rounds of questionnaires administered to experts. After each round, anonymous feedback is provided on the experts' forecasts, prompting them to adjust their responses based on their peers' input. This iterative process aims to achieve group consensus as the range of responses narrows progressively. This cycle repeats several times until a consensus is reached, with the mean scores from the final rounds determining the outcome. While the conventional Delphi Method provides a robust framework, it grapples with issues of ambiguity and uncertainty in both survey questions and responses [54]. One approach to address these challenges is the integration of fuzzy set theory with the traditional Delphi Method [55]. This integration introduced the concept of the "gray zone," the overlapping region of triangular fuzzy numbers, to establish the maximum membership degree and the FDM. Among the popular methods for ranking fuzzy numbers is the α -cut method [56]. The FDM, a refined measurement approach building upon the foundational Delphi Method, was first introduced by Kaufman and Gupta in 1988. It merges fuzzy set theory with the core principles of the Delphi method [57], making it particularly well-suited for constructing models or guidelines [58]. FDM requires subject matter experts relevant to the study's context, enhancing its effectiveness as a measurement approach and helping to resolve uncertainties in the subject under investigation. FDM's versatility is evident in its application across various domains [59–64].

2.2. ISM

ISM is a dynamic learning process that integrates disparate yet directly interrelated elements into a comprehensive and systematic model [65–67]. This tool, rooted in social science management decision-making systems, addresses challenges by analyzing diverse data, synthesizing model elements, and interpreting correlations using binary logic from discrete mathematics. The resulting hierarchical structure visually represents relationships between elements, utilizing principles from graph theory. ISM employs these structures to ascertain the influence and significance of inter-element relationships at each level. When dealing with a problem structure that lacks clarity, Warfield [68] introduced ISM as a method to discern the structural correlations by constructing a model through information integration. As system complexity grows with an expanding structure, ISM becomes indispensable in facilitating model construction [69]. ISM is increasingly recognized across diverse fields for revealing interconnections among various elements related to specific issues [70–79].

2.3. FANP

Saaty introduced the Analytic Hierarchy Process (AHP) in his book. *The Analytic Hierarchy Process* [80]. AHP operates under the assumption that criteria (influential factors)

at the same level are independent of one another. However, recognizing that this assumption does not align with real-world scenarios, Thomas L. Saaty addressed this concern in his subsequent publication, *The Analytic Network Process* [81]. In this work, he extended AHP by incorporating dependencies and feedback mechanisms. The Analytic Network Process (ANP) is a broader framework encompassing AHP, representing decision-making problems as networks of factors, including criteria and alternatives grouped into clusters. ANP accommodates complex interrelationships and feedback within and between clusters, allowing all elements in the network to potentially relate to each other. Researchers can discern relationships among criteria within and among clusters, deducing the priority of alternatives [81]. FANP, which integrates ANP with fuzzy theory, has been favored in previous studies for addressing complex decision-making models and selecting optimal alternatives or strategies based on fuzzy weights. This integration reflects the group's consensus on the criteria's importance, making FANP a popular MCDM model for diverse applications, including project, supplier, and location selection [82–88]. Several scholars have successfully integrated ISM and FANP to facilitate decision-making in various domains. For instance, Chen et al. [89] employed ISM and FANP to enhance the decision-making process for investments in new products within the Thin-Film Transistor Liquid Crystal Display (TFT-LCD) industry, optimizing their benefits and advantages. Sangari et al. [90] introduced an integrated methodology, combining ISM and FANP to analyze factors related to supply chain resilience (SCRes). This approach not only identified these factors but also elucidated their interrelationships, pinpointing the most influential prerequisites for achieving a more resilient supply chain. Many authors have used ISM and FANP to determine important factors in various fields [91–95].

3. Methodology

This research develops a comprehensive MCDM model for human resource recruitment in Taiwan's manufacturing industry amidst labor shortages, using the FDM, ISM, and FANP. This process guides decision-making and establishes final recruitment priorities for the Taiwan electronics manufacturing industry. The study follows a four-phase approach. In the first phase, the study gathers and analyzes factors influencing workforce selection from related studies and expert insights. The second phase involves refining criteria and sub-criteria using the FDM, which determines critical criteria and sub-criteria while eliminating less important ones. Moving to the third phase, the study utilizes the ISM technique to delineate relationships among criteria (outer dependencies) and sub-criteria (inner dependencies) based on expert input. Finally, in the fourth phase, the study employs the FANP to compute weights for all criteria, thereby revealing the priority of critical success factors in labor recruitment. A visual representation of the entire MCDM research flowchart is provided in Figure 1.

The methodology employed in this study unfolds through the following sequential steps:

3.1. Identify Recruitment Criteria in Taiwan's Electronics Manufacturing Industry

The study begins with literature reviews and expert interviews to identify the critical aspects and criteria for the recruitment process in Taiwan's electronics manufacturing industry. Five criteria and thirty-six sub-criteria were identified. The criteria were selected based on an extensive literature review and consultations with industry experts to ensure relevance and validity. The focused was on factors pertinent to the unique challenges of the Taiwanese electronics manufacturing industry, such as technological advancements and labor market conditions. This approach ensures that the criteria are comprehensive, contextually relevant, and robust for effective workforce recruitment (Table 1).

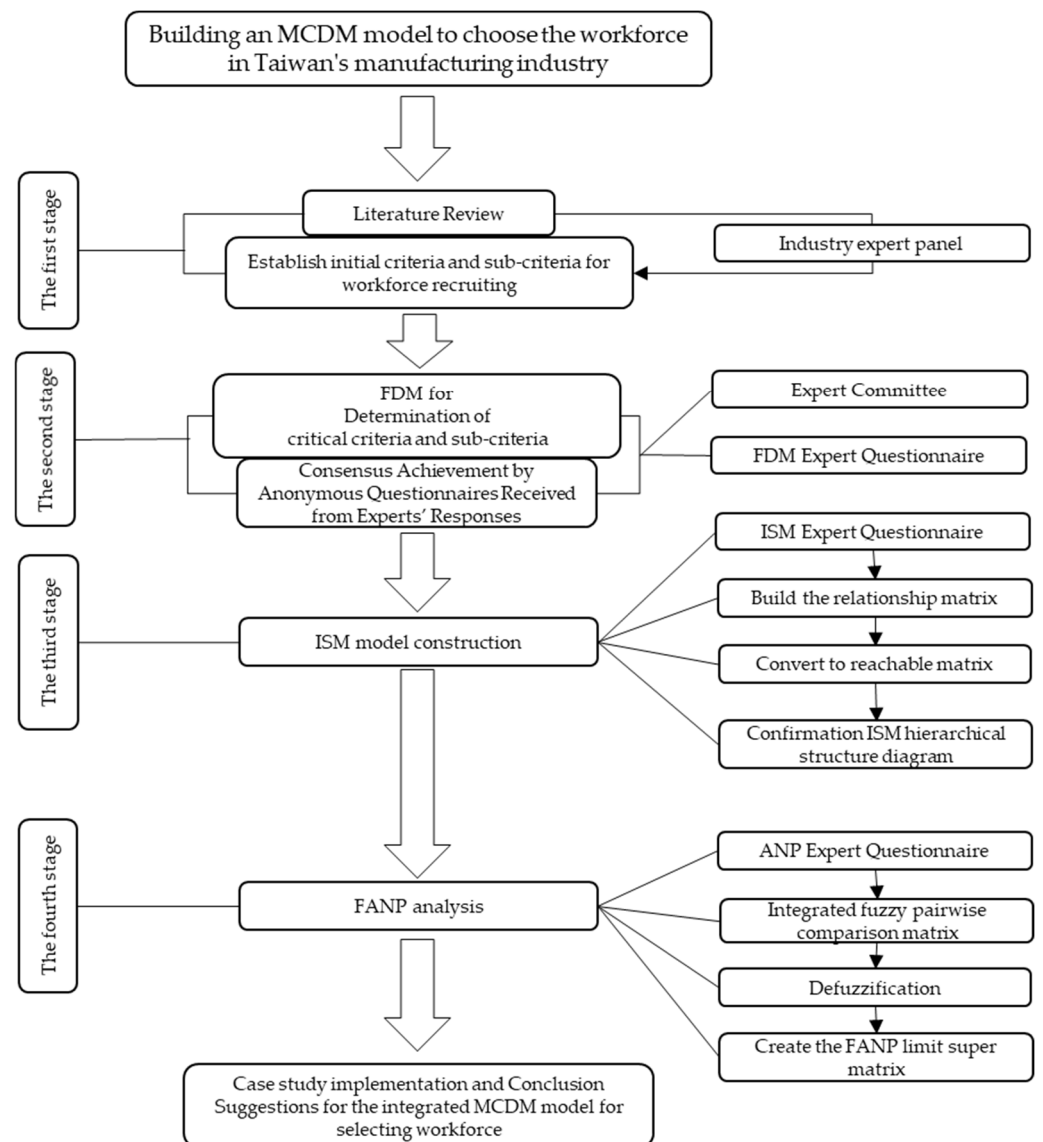


Figure 1. Enhancing decision-making in Taiwan's electronics manufacturing industry: research flowchart.

Table 1. Main criteria and sub-criteria for recruiting workforce in the manufacturing industry.

Criteria	Sub-Criteria	References
C1 Work attitude	S1 Willingness to engage in night shift	[11,96–98]
	S2 Overtime cooperation	[96]
	S3 Discipline compliance	[96]
	S4 Willingness to engage in shifts	[11,96–99]
	S5 Personal and work morality	[7,96,99]
	S6 Patience and calm	[96,100]
	S7 Flexible and open to change	[11,96–98,100]
	S8 Positive	[96,101]
	S9 Loyalty	[7,96,102]
	S10 Docility	[96,103]
C2 Recruitment difficulty	S11 Recruitment lead time	[7,23,98]
	S12 Recruitment competitiveness in the industry	[7,98,104]
	S13 Turnover rate	[7,20,98,104,105]
	S14 Recruitment fee	[7,23,98,104]

Table 1. Cont.

Criteria	Sub-Criteria	References
C3 Work quality	S15 Finish the job in time	[11,96,100,106]
	S16 Ensure the quality of work	[11,96,100,106]
	S17 Effectively control progress	[11,96,100,106]
	S18 Familiarity of relevant knowledge	[7,11,96,107]
	S19 Close residence to the company	[7,11,108]
C4 Environmental adaptation and attendance	S20 Maintaining and protecting work area	[96,109]
	S21 Following healthy and safety procedures	[7,96,97,110]
	S22 Language communication	[96,111]
	S23 Cultural difference	[96,112]
	S24 Regularity of working hours	[96,113]
	S25 Punctuality of working hours	[96,114]
C5 Work ability	S26 Teamwork	[96,115]
	S27 Operating machinery	[7,14,96–99]
	S28 Ability to follow instructions	[7,96,97,116]
	S29 Concentration—attention to detail	[7,96,97,117]
	S30 Experience	[7,96,118]
	S31 Education	[96,119]
	S32 Critical thinking	[7,96,120]
	S33 Interest and aptitude for technology	[7,14,96,99]
	S34 Ability to be cross-trained	[11,14,96,97,100]
	S35 Basic math	[96,120]
	S36 Basic computer skills	[7,96,121]

3.2. Define Initial Criteria and Sub-Criteria: Constituting an Expert Committee and Analyzing Survey Responses Using FDM

The study employs the FDM to gather consensus and merge individual judgments. FDM was chosen for its capability to manage the complexities and uncertainties inherent in decision-making, particularly in the context of workforce recruitment within the Taiwanese electronics manufacturing industry.

This methodology facilitated the systematic inclusion of expert opinions and judgments, ensuring that the identified criteria were comprehensive and aligned with industry needs. Additionally, the FDM's fuzzy nature allowed for the consideration of imprecise and ambiguous information, a common occurrence in real-world decision-making, thereby enhancing the robustness and applicability of the research findings. After collecting all the criteria and sub-criteria from literature reviews and expert interviews, an expert committee is formed to analyze survey responses using the FDM. This process aims to eliminate less important criteria and retain the most significant ones. Experts initially complete a questionnaire with their suggestions, followed by iterative discussions until a consensus is reached. A panel of 12 specialists participated in the FDM survey, including four academics and eight industry experts, each with an average of 10 years of experience (Table 2).

3.2.1. Conduct the Questionnaire and Assigning Values to Criteria

Once the initial criteria and sub-criteria have been defined, this study will identify the pivotal criteria that can significantly impact the workforce recruitment process.

The first questionnaire will be conducted, asking domain experts to select and assign a fuzzy number ranging from 1 to 10 to each factor. The questionnaire is divided into two primary sections: (1) An evaluation of the significance of criteria and sub-criteria that exert influence on the recruitment process, and (2) a segment dedicated to collecting fundamental information about the backgrounds of the participating experts.

Table 3 provides a partial glimpse of the FDM questionnaire. Respondents were tasked with indicating a “most probable range (on a scale of 1–10)” to signify the importance of each item (criteria/sub-criteria) based on their expert judgment.

Table 2. Expert member background.

No	Company	Department	Job Title
1	Hsingwu university of science and technology	Applied English	Acting director
2	Hsingwu university of science and technology	Business Administration	Professor
3	Hsingwu university of science and technology	Audit office	Director
4	Wistron Information Technology & Services Corporation	Human resource	Manager
5	Wistron Information Technology & Services Corporation	Talent Recruitment Department	Director
6	Hsingwu university of science and technology	Tourism	Dean
7	International Trust Machines Corporation	Strategy	Advisor
8	LifeOS Genomics	Administration	Director
9	GWC Group, Taisil branch	Human Resource	Admin
10	Wistron Information Technology & Services Corporation	Human Resource	Manager
11	GWC Group, Sino-German Branch	Human Resource	Director
12	GWC Group, Sino-German Branch	Human Resource	Manager

Table 3. Partial list of the FDM questionnaire.

Criteria/Sub Criteria	Most Possible Range		
	Degree of Importance	Acceptable Maximum Value	Acceptable Minimum Value
Flexible to change	6	7	4
Teamwork	7	8	5
Experience	8	9	6
Critical thinking	9	10	8

For example, if an expert deemed that the item “flexibility to change” should be rated with an importance range between 4 (minimum) and 7 (maximum), they would duly record these two numbers, 4 and 7, respectively.

3.2.2. Apply Fuzzy Set Theory

Utilize fuzzy set theory to obtain a three-point estimate $S^i = \{ (C_k^i, M_k^i, O_k^i) \}$ where S^i should be an integer; C_k^i , M_k^i and O_k^i are the conservative, moderate, and optimistic values, respectively, for the criterion u_i to be scored by the expert k [122].

3.2.3. Create Triangular Fuzzy Numbers

Organize the expert opinions collected from questionnaires into estimates and create the triangular fuzzy number $\tilde{T}$ as follows [123]:

$$\begin{aligned}\tilde{T}_i &= (L_i, M_i, U_i) \\ L_i &= \min (C_k^i) \\ U_i &= \max (O_k^i)\end{aligned}$$

where $L_i = \min(C_k^i)$ is the minimum value among all experts' appraisals for criterion i , $U_i = \max(O_k^i)$ is the maximum value among all experts' appraisals for criterion i , M_i is the geometric mean of all experts' appraisals for criterion i

$$M_i = \sqrt[n]{\prod_{k=1}^n M_k^i}, \text{ } u_i \text{ denotes the } i\text{th criterion } i = 1, 2, \dots, n$$

L_i represents the lowest appraisal value given by the experts for criterion i ; M_i represents the most likely value (geometric mean) of the experts' appraisals for criterion i , and U_i represents the highest appraisal value given by the experts for criterion i .

3.2.4. Calculate Extreme Values for Criteria

For each criterion u_i , calculate the lowest (L_i) and highest (U_i) values of all experts' judgments. Retain the extreme values that satisfy the following Equation (1):

$$\begin{aligned} \mu + 2\sigma &\geq L_i > \mu - 2\sigma \\ \mu + 2\sigma &\geq U_i > \mu - 2\sigma \end{aligned} \quad (1)$$

Following the computation process, all the assigned values conform to Equation (1).

3.2.5. Create and Process Triangular Fuzzy Numbers

The triangular values (the minimum C_L^i , the geometric mean C_M^i and the maximum C_U^i) of the remaining most conservative value C_k^i and the triangular values (the minimum O_L^i , the geometric mean O_M^i and the maximum O_U^i) of the qualified most optimistic value O_k^i are processed in this step and result in a triangular fuzzy number.

As previously mentioned, this study creates two triangular fuzzy numbers, $C^i = (C_L^i, C_M^i, C_U^i)$ and $O^i = (O_L^i, O_M^i, O_U^i)$ for each criterion u_i with a triangular value of the remaining most conservative value C_k^i and the qualified most optimistic value O_k^i . If they overlap, the area of the overlap is the "gray zone" shown in Figure 2.

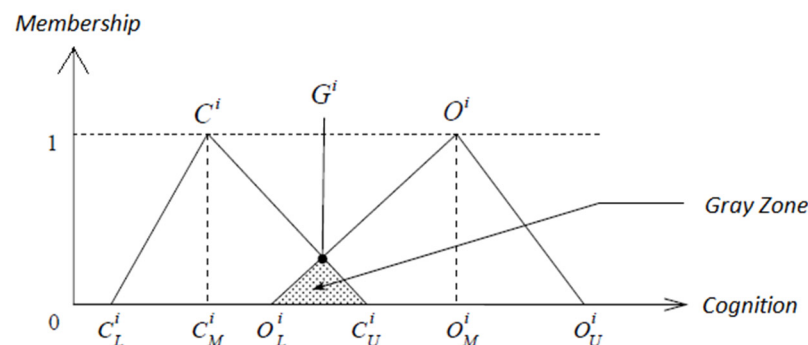


Figure 2. Gray zone in two triangular fuzzy numbers.

3.2.6. Evaluate Consensus for Criteria

Based on the gray zone of each criteria u_i , determine the importance of consensus value G^i and assess if experts have reached a valid consensus. The consensus value G^i indicates the important a criteria u_i is. A higher the value G^i signifies a more critical criterion u_i . After obtaining the C_U^i and O_L^i from step 4, the consensus value G^i is calculated as follows:

1. If the two triangles do not overlap ($C_U^i \leq O_L^i$), indicating consensus among the experts, the consensus important value G^i will be the average of C_M^i and O_M^i .

$$G^i = \frac{(C_M^i + O_M^i)}{2} \quad (2)$$

2. If the two triangles overlap ($C_U^i > O_L^i$), creating a gray zone Z^i in the criteria u_i and $Z^i = C_U^i - O_L^i$, and the value between the geometric mean of the most optimistic value and the geometric mean of the most conservative is denoted as $M^i = O_M^i - C_M^i$. The relationship between $M^i = O_M^i - C_M^i$ and $Z^i = C_U^i - O_L^i$, meanwhile, ought to be identified as follows:

- (1) If $Z^i < M^i$, indicates no consensus among experts, but the extreme opinions are not significantly different from the others. In this case, the consensus importance G^i of criterion u_i is calculating using the minimum fuzzy relationship to find the fuzzy sets and then obtaining the maximum membership

degree [124]. The $\mu_F(x_j)$ represented below is the membership function of the fuzzy triangular number C^i and O^i .

$$F^i(x_j) = \left\{ \int_x \left\{ \min \left[C^i(x_j), O^i(x_j) \right] \right\} dx \right\}, j \in U \quad (3)$$

$$G^i = \left\{ x_j | \max \mu_{F^i}(x_j) \right\}, j \in U \quad (4)$$

Formula (4) is the actual calculation for the consensus value G^i which has a gray zone Z^i .

$$G^i = \frac{(C_U^i \times O_M^i) - (O_L^i \times C_M^i)}{(O_M^i - O_L^i) + (C_U^i - C_M^i)} \quad (5)$$

- (2) If $Z^i > M^i$, it indicates a lack of consensus among experts, with extreme opinions significantly differing from the others. Therefore, the criterion u_i which has not converged, will provide experts with the ranging value M^i for the next questionnaire. All the criteria are expected to converge until the consensus value G^i is reached.

3.2.7. Set a Threshold for Criteria Qualification

A threshold S is set to determine if a criteria u_i is qualified. Compare the consensus value G^i with S , if $G^i > S$, the criteria u_i is selected; otherwise, it is eliminated [125]. The threshold S typically ranges from 6.0 to 7.0 according to literature reviews but can be adjusted for better decision-making.

3.3. Utilize the ISM Method to Delineate the Relationships among the Criteria and Sub-Criteria

The ISM method is used to systematically map out and analyze the relationships among criteria and sub-criteria by developing a reachability matrix and a diagram, which visually represents their interdependencies. This approach helps identify key driving and dependent factors, aiding in more informed decision-making for workforce recruitment in the Taiwanese electronics manufacturing industry. This involves establishing a hierarchical structure that reflects the interconnections between criteria and sub-criteria. Additionally, the ISM method generates a network relationship map, which is executed in a series of defined steps within this study.

3.3.1. Create the Adjacency Matrix

In this initial step, an adjacency matrix illustrating the contextual relationships among the sub-criteria within each criterion is created.

To accomplish this, questionnaires are initially designed to identify the contextual connection between any two criteria and the direction of this relationship. The experts' judgments on the relationship between each pair of criteria are recorded and tallied. A threshold value of 88% is employed to determine the dependency between criteria. Specifically, if the frequency of agreement among experts is less than 88%, a value of 0 is assigned, signifying no influence between the criteria. Conversely, if the frequency of expert agreement is 88% or greater, a value of 1 is assigned, indicating a recognized influence between the criteria. For instance, there are n criteria in an adjacency matrix, e_i and e_j are, respectively, the i th and the j th sub-criteria of criteria, and π_{ij} is the relation between the i th and the j th criteria

of the aspect. If e_i influences e_j , then $\pi_{ij} = 1$; otherwise, $\pi_{ij} = 0$. The adjacency matrix D will be presented as the following formulation:

$$D = \begin{matrix} & \begin{matrix} e_1 & e_2 & \vdots & e_n \end{matrix} \\ \begin{matrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{matrix} & \begin{bmatrix} 0 & \pi_{12} & \cdots & \pi_{1n} \\ \pi_{21} & 0 & \cdots & \pi_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{m1} & \pi_{m2} & \cdots & 0 \end{bmatrix} \end{matrix} \quad (6)$$

3.3.2. Create the Reachability Matrix

This phase involves creating the reachability matrix and checking for transitivity. Initially, an initial reachability matrix M is computed by combining the matrix D from the previous step with a unit matrix I , as shown in Formula (6). Subsequently, the final reachability matrix M^* is determined using Boolean multiplication and addition operations, as outlined in Table 4. This matrix M^* is further subjected to a convergence process, as depicted in Formula (7) [126].

$$M = D + I \quad (7)$$

$$M^* = M^k = M^{k+1} \quad k > 1 \quad (8)$$

Table 4. Boolean logic.

Boolean Logic	Operator	Operator	Operand
Intersect	AND	+	0, 1
Union	OR		0, 1
Except	NOT	-	0, 1

The reachability matrix M^* depicts all the interdependencies among criteria and sub-criteria. Finalize the ISM structural modeling using the hierarchy matrix.

3.4. Determine the Weights of Criteria and Sub-Criteria in Workforce Recruitment Using FANP

The FANP method is applied to determine the weights of criteria and sub-criteria by analyzing their relative importance and interdependencies. This process involves constructing pairwise comparison matrices and synthesizing the results to prioritize factors crucial for workforce recruitment in the Taiwanese electronics manufacturing industry. To construct the FANP questionnaire, this study adopts the nine-point relative importance scale introduced by Saaty in 1980. The survey is administered to experts who serve as decision-makers within the manufacturing industry. The FANP is chosen for its ability to handle the nonlinear relationships and uncertainties inherent in decision-making, particularly in workforce recruitment for Taiwanese electronics manufacturing. It incorporates fuzzy logic to capture the complexities of human judgments and interdependencies among criteria. This method provides a structured approach, enhancing the credibility of research findings by systematically modeling relationships and determining relative importance weights. The FANP methodology is subsequently executed as follows [127].

3.4.1. Construction of a Pairwise Comparison Matrix of Expert Opinions

1. Design and administration of the FANP expert questionnaire

In this step, the hierarchical relationship diagram is used to compare criteria and sub-criteria in pairs. A questionnaire is designed based on these comparisons, and experts are asked to rate the importance of each pairwise comparison. This process ensures that assessments consider both the gradient of influence and intensity, improving the consistency of results.

2. Creation of pairwise comparison matrix

When comparing elements in pairs, the evaluation values range from 1, 2, ..., 9, 1/2, ..., 1/9. The values represent increasing levels of importance. The upper triangular area of the matrix contains these values, while the main diagonal is set to 1 to indicate self-comparisons. The lower triangular area of the matrix contains the reciprocal values of the upper triangular area. This process generates the matrix A , as shown in Equation (9).

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{21} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix} \quad (9)$$

3.4.2. Apply Fuzzy Theory to Convert Expert Opinions into Fuzzy Sets

1. Establish a Fuzzy Pairwise Comparison Matrix

This study employs standard triangular fuzzy numbers for conversion, characterized by symmetric fuzzy numbers with a center value of 0 and a spread of 1. Each scale is represented by an interval of ± 1 . For example, the scale $\tilde{5} = (4, 5, 6)$, and the triangular fuzzy reciprocal of $\tilde{\frac{1}{5}} = (1/6, 1/5, 1/4)$. If the three points of the equilateral triangle are (X, Y, Z) , the fuzzy pairwise comparison matrix is represented by Formula (10). The detailed comparison table before and after conversion is shown in Table 5 [128].

$$\tilde{A} = \begin{bmatrix} 1 & (X_{12}, Y_{12}, Z_{12}) & \cdots & (X_{1n}, Y_{1n}, Z_{1n}) \\ (1/Z_{12}, 1/Y_{12}, 1/X_{12}) & 1 & \cdots & (X_{2n}, Y_{2n}, Z_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ (1/Z_{1n}, 1/Y_{1n}, 1/X_{1n}) & (1/Z_{2n}, 1/Y_{2n}, 1/X_{2n}) & \cdots & 1 \end{bmatrix} \quad (10)$$

Table 5. Comparison table before and after conversion of standard triangular fuzzy numbers.

Traditional ANP	Linguistic Variables	Triangular Fuzzy Number	Triangular Fuzzy Number Reciprocal Value
1	Equally important	(1, 1, 2)	(1/2, 1, 1)
2	~	(1, 2, 3)	(1/3, 1/2, 1)
3	Slightly important	(2, 3, 4)	(1/4, 1/3, 1/2)
4	~	(3, 4, 5)	(1/5, 1/4, 1/3)
5	Important	(4, 5, 6)	(1/6, 1/5, 1/4)
6	~	(5, 6, 7)	(1/7, 1/6, 1/5)
7	More important	(6, 7, 8)	(1/8, 1/7, 1/6)
8	~	(7, 8, 9)	(1/9, 1/8, 1/7)
9	Very important	(8, 9, 9)	(1/9, 1/9, 1/8)

2. Integration of expert opinions

The following formula explains the process of integrating expert opinions using the geometric mean method:

$\tilde{T}_{ij}$ represents the triangular fuzzy number after integration and $\tilde{M}$ denotes the result matrix after integrating n fuzzy pairwise comparison matrices, as shown in Formula (11) [129–131].

$$\tilde{T}_{ij} = \sqrt[n]{\tilde{t}_{ij1} \otimes \tilde{t}_{ij2} \otimes \cdots \otimes \tilde{t}_{ijn}} \quad \tilde{M} = \begin{bmatrix} \tilde{1} & \cdots & \tilde{t}_{1n}' \\ \vdots & \ddots & \vdots \\ \tilde{t}_{n1}' & \cdots & \tilde{1} \end{bmatrix} \quad (11)$$

3. Convert fuzzy values into crisp values

The purpose of converting the integrated fuzzy values from expert opinions into equivalent precise values is to render them more understandable and usable. Common methods for this conversion include the Center of Gravity Method, the Distance Method, the Mean of Maximum Method, and the Fuzzy Ranking Method. Among these, the Center of Gravity Method is the simplest and most frequently used [132]. This study also uses the Center of Gravity Method, which calculates the central value of a fuzzy set to represent its precise value. The operational formula for this conversion using the Center of Gravity Method is explained as follows:

$$DF_{ij} = \left[(\widetilde{Y}_{ij} - \widetilde{Z}_{ij}) + (\widetilde{Z}_{ij} - \widetilde{X}_{ij}) \right] / 3 + \widetilde{X}_{ij} \quad (12)$$

where $\widetilde{X}_{ij}$, $\widetilde{Y}_{ij}$, $\widetilde{Z}_{ij}$ are fuzzy numbers, $\widetilde{X}_{ij}$ is the most likely value (the center value) of the fuzzy number, $\widetilde{Y}_{ij}$ and $\widetilde{Z}_{ij}$ represent the lower and upper bounds of the fuzzy number, respectively.

3.4.3. Priority Vector Algorithm

In 1986, Saaty and Takizawa proposed using matrix multiplication to derive weights that address the interdependence and feedback relationships between factors and criteria [80]. They combined the weight vectors of factors and criteria to calculate the actual weights of factors and the overall weight value. The evaluation steps are as follows:

- Step 1. Calculate the independent weights of each aspect under the research objective;
- Step 2. Calculate the relationship weights between dependent aspects;
- Step 3. Calculate the independent weights of elements under each aspect;
- Step 4. Calculate the relationship weights between dependent elements;
- Step 5. Calculate the actual weights of each aspect and each element, as well as the overall weights;
- Step 6. Rank and compare competitive strategies based on the weights of each element.

1. Calculation and Consistency Test:

Proportion vector (w_i) and maximum eigenvalue ($\lambda_{\max}$)

After constructing the pairwise comparison matrix, the weight vector can be calculated using the column vector geometric mean, as shown in Formula (13) below:

$$\widetilde{Z}_i = \left(\prod_{j=1}^n \widetilde{A}_{ij} \right)^{\frac{1}{n}} \quad \forall_{ij} = 1, 2, \dots, n \quad (13)$$

where $\widetilde{Z}_i$ is the geometric mean of the i th row, $\widetilde{A}_{ij}$ represents the elements of the pairwise comparison matrix. The weight vector (W_i) is then normalized by dividing each geometric mean by the sum of all geometric means:

$$\widetilde{W}_i = \frac{\widetilde{Z}_i}{\sum_{i=1}^n \widetilde{Z}_i} = \frac{\left(\prod_{j=1}^n \widetilde{A}_{ij} \right)^{1/n}}{\sum_{j=1}^n \left(\prod_{j=1}^n \widetilde{A}_{ij} \right)^{\frac{1}{n}}} \quad \forall_{ij} = 1, 2, \dots, n$$

Substitute the above weight vector into the following Formula (14) to obtain the maximum eigenvalue, which allows for consistency testing:

$$A \times w = \lambda_{\max} \times w \quad (14)$$

where A is the pairwise comparison matrix, w is the weight vector, $\lambda_{\max}$ is the maximum eigenvalue, which is used to check the consistency of the pairwise comparisons.

2. Consistency test:

When respondents are completing pairwise comparison questionnaires, they often experience subjective uncertainty, which allows for some degree of inconsistency. However, it is still necessary to test whether there are significant contradictions in the numerical values. Saaty (1980) proposed two steps to test this: the Consistency Index (C.I.) and the Consistency Ratio (C.R.) [133].

a. Consistency Index (C.I.)

$$C.I. = (\lambda_{\max} - n) / (n - 1) \quad (15)$$

b. Consistency Ratio (C.R.)

$$C.R. = C.I. / R.I. \quad (16)$$

R.I. is a random index. The corresponding value can be found according to the order of the matrix, as shown in Table 6.

Table 6. R.I. table.

n	1	2	3	4	5	6	7	8	9	10
R.I.	0	0	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

3. Calculate weights:

Calculate the weight of elements relative to the overall hierarchy [80];

Independent weight matrix of each aspect under the research objectives: W1;

Relationship weight matrix between dependent facets: W2;

Independent weight matrix of the elements under each aspect: W3;

Relationship weight matrix between dependent elements: W4;

$$\text{Actual weight of each aspect: } W_{\text{goal-component}} = W2 \times W1 \quad (17)$$

$$\text{The actual weight of the elements under each aspect: } W_{\text{component-element}} = W4 \times W3 \quad (18)$$

The overall weight value of each element to the research goal:

$$W_{\text{goal-element}} = W_{\text{goal-component}} \times W3 \quad (19)$$

$$W = \begin{matrix} & \begin{matrix} \text{Goal} \\ \text{Aspect} \\ \text{Component} \end{matrix} & \begin{bmatrix} 0 & 0 & 0 \\ W1 & W2 & 0 \\ 0 & W3 & W4 \end{bmatrix} \end{matrix}$$

The Analytic Network Process (ANP) priority vector algorithm can reveal the significance of three aspects:

1. The actual weights of each aspect ($W_{\text{goal_component}}$) indicate the degree of influence each aspect has on the goal;
2. The actual weights of elements under each aspect ($W_{\text{component_element}}$) can be used to deduce the influence of each element within its respective aspect;
3. The overall weight values of each element for the goal ($W_{\text{goal_element}}$) ultimately summarize the importance of each element's impact on the overall goal, leading to corresponding specific recommendations.

3.4.4. Ranking and Identifying Optimal Criteria and Sub-Criteria

Rank the weight values obtained from FANP to identify the optimal criteria and sub-criteria. Additionally, pinpoint the key factors that Taiwan manufacturing firms prioritize when selecting personnel, offering valuable guidance to decision-makers.

4. Findings

Given the robust demand for labor and the fierce competition in the global market, manufacturing enterprises must meticulously select the right workforce to gain a competitive

edge. An effective MCDM model for personnel selection can empower management teams in manufacturing enterprises to optimize their chances of selecting the most suitable talent. This study aims to introduce a comprehensive MCDM model for workforce assessment.

4.1. Use FDM to Identify Key Criteria and Sub-Criteria for Workforce Recruitment Decisions

In this study, the FDM analysis reveals that one criterion and two sub-criteria exhibit no overlap (no gray zone). The outcomes of the consensus value G_i , along with the presence of a gray zone Z_i , perform Equation (2) results are shown in Table 7. The results of Equations (3)–(5) are shown in Table 8.

Table 7. The consensus value G_i without a gray zone.

Criteria	Sub Criteria	C_M^i	O_M^i	G^i	$C_U^i - O_L^i = Z^i$
Work attitude	Positive (S8)	6.333	9.417	7.875	0.000
Work quality	Effectively control progress (S17)	6.583	9.417	8	0.000

Table 8. The consensus value G_i with a gray zone.

Criteria/Sub-Criteria	C_L^i	C_M^i	C_U^i	O_L^i	O_M^i	O_U^i	G
Work attitude (C1)	5	2.757	10	8	9.75	10	10.393
Recruitment difficulty (C2)	2	2.933	7	4	7.583	10	6.522
Work quality (C3)	4	2.088	8	7	8.833	10	7.050
Work ability (C5)	4	2.558	8	7	9.166	10	6.622
Willingness to engage in night shift (S1)	1	4.000	7	3	7.333	10	NO
Overtime cooperation (S2)	3	5.583	7	3	8.583	10	NO
Discipline compliance (S3)	5	7.000	10	9	9.750	10	9.200
Willingness to engage in shifts (S4)	1	5.333	7	3	8.083	10	NO
Personal and work morality (S5)	5	6.667	9	8	9.500	10	8.391
Patience and calm (S6)	4	6.083	8	7	8.833	10	7.489
Flexible and open to change (S7)	3	6.000	8	7	8.917	10	7.489
Loyalty (S9)	5	6.417	8	7	9.250	10	7.587
Docility (S10)	3	6.000	10	6	8.833	10	NO
Recruitment lead time (S11)	3	5.250	7	5	7.917	10	NO
Recruitment competitiveness in the industry (S12)	1	5.250	7	1	7.833	10	NO
Turnover rate (S13)	1	5.250	7	1	8.083	10	NO
Recruitment fee (S14)	1	5.250	7	1	7.417	10	NO
Finish job in time (S15)	5	6.583	8	7	9.250	10	7.614
Ensure the quality of work (S16)	5	6.667	9	8	9.333	10	8.364
Effectively control progress (S17)	4	6.583	8	8	9.417	10	8
Familiarity of relevant knowledge (S18)	3	6.500	10	8	9.250	10	8.526
Close residence to the company (S19)	1	4.333	7	1	7.000	10	NO
Maintaining and protecting work area (S20)	3	9.455	8	3	8.167	10	NO
Following healthy and safety procedures (S21)	4	6.250	8	5	8.500	10	7.361
Language communication (S22)	3	5.583	8	3	8.083	10	7.125
Cultural difference (S23)	1	4.833	7	1	7.750	10	NO
Regularity of working hours (S24)	3	6.000	8	6	8.833	10	7.346
Punctuality of working hours (S25)	5	6.583	8	6	9.000		7.358
Teamwork (S26)	5	6.750	9	5	9.333	10	NO
Operating machinery (S27)	1	5.167	7	5	8.417	10	6.302
Ability to follow instructions (S28)	4	6.167	8	6	8.750	10	7.200
Concentration—attention to detail (S29)	4	6.083	8	6	8.750	10	7.179
Experience (S30)	2	5.000	7	5	8.083	10	6.213
Education (S31)	2	5.083	10	5	7.917	10	NO
Critical thinking (S32)	4	5.667	8	7	8.750	10	7.429
Interest and aptitude for technology (S33)	4	5.833	10	6	8.417	10	NO
Ability to be cross-trained (S34)	5	6.083	10	6	9.000	10	NO
Basic math (S35)	1	4.333	7	1	7.333	10	NO
Basic computer skills (S36)	3	5.000	8	5	8.083	10	6.521

In this research, a threshold value of 6 was applied. Following this elimination process, the critical criteria and sub-criteria were identified, comprising four main criteria and 13 sub-criteria, all of which exceeded the established threshold. Consequently, 4 out of the initial 5 criteria and 13 out of the initial 36 sub-criteria were retained after the threshold was established.

4.2. Assess Interdependencies among Identified Criteria/Sub-Criteria Using ISM

In this phase, the ISM method was employed to construct a hierarchical structure, considering the relationships among the four criteria and thirteen sub-criteria. The ISM methodology recommends the use of group discussions, and thus, the same twelve experts are engaged. This approach is to discern the nature of contextual relationships among these factors. Additionally, ISM aids in creating a network relationship map.

After applying Formula (6), the reachability matrix M^* (Table 9) is obtained through the convergence process applied to the initial reachability matrix M (Formulas (7) and (8)).

Table 9. The final reachability matrix M^* for sub-criteria.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13
S1	1	1	1	1	1	0	1	1	0	0	1	1	1
S2	1	1	1	1	0	0	1	1	0	0	1	1	1
S3	1	1	1	1	1	0	0	0	0	0	1	1	1
S4	1	1	1	1	1	0	0	0	0	0	1	1	1
S5	1	1	1	1	1	0	0	0	0	0	1	1	1
S6	0	0	1	1	1	1	0	0	0	0	0	0	1
S7	1	1	1	1	1	0	1	0	0	0	1	1	1
S8	1	1	1	1	1	0	0	1	0	1	1	1	1
S9	0	0	1	1	1	1	0	0	1	0	0	0	1
S10	0	0	1	1	1	0	0	1	0	1	0	0	1
S11	1	1	1	1	1	0	1	1	0	0	1	1	1
S12	1	1	1	1	0	0	1	1	0	0	1	1	1
S13	1	1	1	1	1	0	0	0	0	0	1	1	1

After constructing the reachability matrix and answering all questions, a hierarchical structure is established (Figure 3). This structure, based on the reachability matrix M^* , illustrates relationships between sub-criteria within the same cluster (criteria) and among sub-criteria across different clusters, as well as dependencies between clusters under the overarching goal. The structure includes arrows indicating the direction of relationships between factors. For instance, an arrow originating from Criteria C1 extends to Criteria C2, C3, and C4, indicating that C1 (Work Attitude) influences C2 (Work Quality), C3 (Environmental Adaptation and Attendance), and C4 (Work Ability). The interdependence between criteria and sub-criteria for workforce selection is clarified in Figure 4.

4.3. Determine Relative Weights and Rank of Critical Criteria and Sub-Criteria for Workforce Selection Using FANP

ISM results reveal interdependencies among criteria and sub-criteria, further analyzed using FANP. The FANP method calculates hierarchical weights through paired comparisons and multiple assessments, highlighting key factors in workforce selection for Taiwan's electronics manufacturing company. Experts rate these elements through pairwise comparisons on a 9-point scale, with resulting weights guiding decision-making.

4.3.1. Construct a Pairwise Comparison Matrix of Expert Opinions

An illustrative example of a pairwise comparison matrix derived from an expert's assessment of the four criteria is presented in Table 10 (Formula (9)).

Criteria	Dependence
C2 Work quality	C1 Work Attitude, C3 Environmental Adaption and Attendance, C4 Work Ability
C3 Environmental adaption and attendance	C1 Work Attitude, C2 Work Quality
C4 Work ability	C1 Work Attitude
Sub-criteria	Dependence
S1 Discipline compliance	S4 Finish the job in time, S5 Ensure the quality of work, S7 Familiar with relevant knowledge, S8 Following healthy and safety procedures, S11 Ability to follow instructions, S12 Concentration- attention to detail, S13 Critical thinking
S2 Personal and work morality	S4 Finish the job in time, S5 Ensure the quality of work, S7 Familiar with relevant knowledge, S8 Following healthy and safety procedures, S11 Ability to follow instructions, S12 Concentration- attention to detail, S13 Critical thinking
S3 Positive	S4 Finish the job in time, S5 Ensure the quality of work, S6 Effectively control progress, S7 Familiar with relevant knowledge, S9 Regularity of working hours, S10 Punctuality of working hours, S11 Ability to follow instructions, S12 Concentration- attention to detail, S13 Critical thinking
S4 Finish the job in time	S1 Discipline compliance, S2 Personal and work morality, S3 Positive, S8 Following healthy and safety procedures, S9 Regularity of working hours, S10 Punctuality of working hours, S11 Ability to follow instructions, S12 Concentration- attention to detail, S13 Critical thinking
S5 Ensure the quality of work	S1 Discipline compliance, S3 Positive, S8 Following healthy and safety procedures, S9 Regularity of working hours, S10 Punctuality of working hours, S11 Ability to follow instructions, S13 Critical thinking
S6 Effectively control progress	S9 Regularity of working hours
S7 Familiar with relevant knowledge	S1 Discipline compliance, S2 Personal and work morality, S11 Ability to follow instructions, S12 Concentration- attention to detail
S8 Following healthy and safety procedures	S1 Discipline compliance, S2 Personal and work morality, S11 Ability to follow instructions, S12 Concentration- attention to detail
S11 Ability to follow instructions	S1 Discipline compliance, S2 Personal and work morality, S3 Positive, S4 Finish the job in time, S5 Ensure the quality of work, S7 Familiar with relevant knowledge, S8 Following healthy and safety procedures
S12 Concentration- attention to detail	S1 Discipline compliance, S2 Personal and work morality, S3 Positive, S4 Finish the job in time, S5 Ensure the quality of work, S7 Familiar with relevant knowledge, S8 Following healthy and safety procedures
S13 Critical thinking	S1 Discipline compliance, S2 Personal and work morality, S3 Positive, S4 Finish the job in time, S5 Ensure the quality of work, S6 Effectively control progress, S7 Familiar with relevant knowledge, S8 Following healthy and safety procedures, S9 Regularity of working hours, S10 Punctuality of working hours

Figure 3. Interdependence between the criteria and sub-criteria for workforce selection.

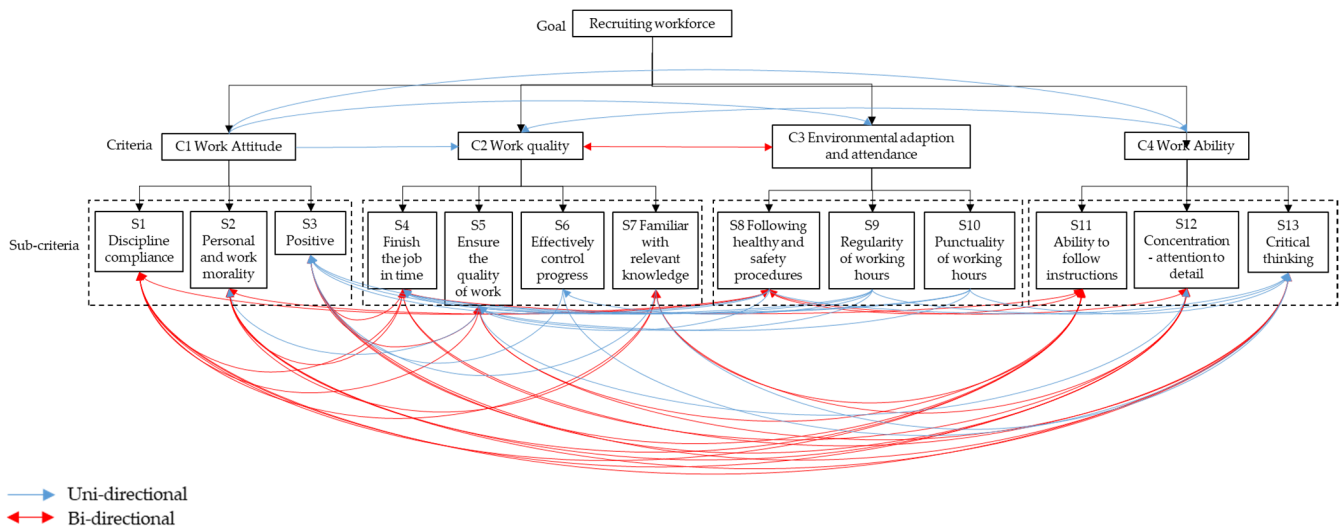


Figure 4. The relationship diagram of the impact of the ISM level on the recruiting workforce for the manufacturing industry.

Table 10. Pair-wise comparison matrix (expert 1).

Recruiting Workforce	C1	C2	C3	C4
C1	1	1/4	1/3	1/2
C2	4	1	1/4	1/3
C3	3	4	1	3
C4	1/2	3	1/3	1

4.3.2. Apply Fuzzy Theory to Convert Expert Opinions into Fuzzy Sets

Table 11 provides an illustration of the fuzzy pairwise comparison matrix derived from the evaluations of 12 experts regarding the four criteria (Formula (10)). Table 12 combines the decision-makers' opinions and presents the results after converting fuzzy sets into crisp values. (Formulas (11) and (12)).

Table 11. Fuzzy pairwise comparison matrix (12 experts).

Recruiting Workforce	C1	C2	C3	C4
C1	(1·1·1)	(2.285·3.333·4.333)	(1·1.600·2.500)	(1.600·2.625·3.625)
C2	(0.250·0.333·0.428)	(1·1·1)	(1.400·2·2.889)	(1·1.444·2)
C3	(0.400·0.625·1)	(0.333·0.500·0.714)	(1·1·1)	(1.111·1.666·1.500)
C4	(0.285·0.375·0.625)	(0.500 0.666 1)	(0.400·0.600·1)	(1·1·1)

Table 12. Result after converting fuzzy sets into crisp values.

Recruiting Workforce	C1	C2	C3	C4
C1	1.000	3.300	1.685	2.614
C2	0.324	1.000	2.076	1.481
C3	0.678	0.526	1.000	1.757
C4	0.429	0.731	0.637	1.000

4.3.3. Priority Vector Algorithm

Examine the Consistency

After obtaining the eigenvectors, the largest eigenvalue can be computed for each matrix. Subsequently, the Consistency Index (C.I.), Random Index (R.I.), and Consistency Ratio (C.R.) are calculated. According to Saaty's recommendation, consistency is achieved if the C.R. is less than 0.1. Thus, the responses from the twelve experts are subjected to the described process. The results indicate that all C.R. values are less than 0.1, signifying the validation of the questionnaires (Table 13) (Formulas (13)–(16)).

Table 13. Consistency Test for Criteria.

Recruiting Workforce	C1	C2	C3	C4	Weights
C1	1.000	3.300	1.685	2.614	0.433
C2	0.324	1.000	2.076	1.481	0.222
C3	0.678	0.526	1.000	1.757	0.197
C4	0.429	0.731	0.637	1.000	0.148

Note: $\lambda_{\max} = 4.0543$; C.I. = 0.01811; R.I. = 0.89; C.R. = 0.02034.

Calculate the Weight of Criteria and Sub-Criteria Relative to the Overall Hierarchy

In the previous section, the matrix underwent consistency testing, and the results showed that all evaluation outcomes met consistency requirements after converting fuzzy sets into crisp values. Using geometric mean integration and normalization, the weight vectors were calculated. These were then entered into the matrix, resulting in the following four types of weight vector matrices.

Matrix W1: Independent weight matrix of each criterion under the research objective

$$\begin{matrix} C1 \\ C2 \\ C3 \\ C4 \end{matrix} \begin{bmatrix} 0.154 \\ 0.199 \\ 0.409 \\ 0.237 \end{bmatrix}$$

Matrix W2: Relationship weight matrix between dependent criteria

$$\begin{matrix} . \\ C1 \\ C2 \\ C3 \\ C4 \\ . \end{matrix} \begin{bmatrix} C1 & C2 & C3 & C4 \\ 1 & 0.097 & 0.5 & 0.5 \\ 0 & 0.364 & 0 & 0 \\ 0 & 0.173 & 0.5 & 0 \\ 0 & 0.364 & 0 & 0.5 \\ . & . & . & . \end{bmatrix}$$

Matrix W3: Independent weight matrix of the sub-criteria under each criterion

$$\begin{matrix} S1 \\ S2 \\ S3 \\ S4 \\ S5 \\ S6 \\ S7 \\ S8 \\ S9 \\ S10 \\ S11 \\ S12 \\ S13 \\ . \end{matrix} \begin{bmatrix} 0.458 \\ 0.260 \\ 0.280 \\ 0.084 \\ 0.384 \\ 0.329 \\ 0.201 \\ 0.573 \\ 0.267 \\ 0.158 \\ 0.578 \\ 0.255 \\ 0.168 \\ . \end{bmatrix}$$

Matrix W4: Relationship weight matrix between dependent sub-criteria

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13
S1	0.500	0.333	0.242	0.041	0.056	0.000	0.380	0.2886	0.000	0.000	0.000	0.000	0.000
S2	0.000	0.333	0.242	0.016	0.000	0.000	0.119	0.1388	0.000	0.000	0.000	0.000	0.000
S3	0.000	0.000	0.242	0.022	0.029	0.128	0.000	0.000	0.000	0.000	0.000	0.000	0.000
S4	0.062	0.040	0.000	0.377	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
S5	0.124	0.087	0.071	0.000	0.500	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
S6	0.048	0.044	0.065	0.000	0.000	0.500	0.000	0.000	0.000	0.000	0.000	0.000	0.000
S7	0.000	0.000	0.037	0.000	0.000	0.000	0.500	0.000	0.000	0.000	0.000	0.000	0.000
S8	0.106	0.070	0.000	0.000	0.112	0.000	0.000	0.500	0.000	0.000	0.000	0.000	0.000
S9	0.000	0.000	0.000	0.000	0.051	0.148	0.000	0.000	0.000	0.000	0.000	0.000	0.000
S10	0.076	0.397	0.026	0.0695	0.054	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
S11	0.081	0.051	0.018	0.0783	0.106	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
S12	0.000	0.000	0.023	0.1488	0.083	0.223	0.000	0.000	0.000	0.000	0.000	0.000	0.000
S13	0.000	0.000	0.028	0.244	0.007	0.000	0.000	0.072	0.000	0.000	0.000	0.000	0.000

The final step involves obtaining the evaluation model. To achieve this, each group within the converged matrix must be normalized, allowing the derivation of individual weights. Subsequently, MATLAB is employed to perform the multiplication of the weighted matrix to achieve convergence. The normalized final weights are presented in Table 14 (Equations (17)–(19)).

Table 14. The final relative weight of criteria of the MCDM model for workforce recruitment.

Criteria			Sub-Criteria		
Criteria	Weight	Criteria Ranking	Sub-Criteria Independent Weight	Weight	Sub-Criteria Ranking
C1 Work attitude	0.496	1	S1 Discipline compliance	0.227	1
			S2 Personal and work morality	0.129	4
			S3 Positive	0.139	2
C2 Work quality	0.072	4	S4 Finish the job in time	0.006	13
			S5 Ensure the quality of work	0.028	10
			S6 Effectively control progress	0.023	11
			S7 Familiar with relevant knowledge	0.014	12

Table 14. Cont.

Criteria			Sub-Criteria		
Criteria	Weight	Criteria Ranking	Sub-Criteria Independent Weight	Weight	Sub-Criteria Ranking
C3 Environmental adaption and attendance	0.239	2	S8 Following healthy and safety procedures	0.137	3
			S9 Regularity of working hours	0.064	6
			S10 Punctuality of working hours	0.037	8
C4 Work ability	0.191	3	S11 Ability to follow instructions	0.110	5
			S12 Concentration—attention to detail	0.048	7
			S13 Critical Thinking	0.032	9

5. Discussion

The weightings presented in Table 14 highlight the primary factor to consider when selecting a workforce: Work Attitude (C1). This criterion is closely followed by Environmental Adaptation and Attendance (C3), which ranks as the second most important criterion. Work Ability is identified as the third critical aspect (Table 15).

Table 15. The critical criteria and sub-criteria.

Criteria	Sub Criteria
Work attitude (C1)	Discipline compliance (S1) Personal and work morality (S2) Positive (S3)
Work quality (C2)	Finish the job in time (S4) Ensure the quality of work (S5) Effectively control progress (S6) Familiarity of relevant knowledge (S7)
Environmental adaptation and attendance (C3)	Following healthy and safety procedures (S8) Regularity of working hours (S9) Punctuality of working hours (S10)
Work ability (C4)	Ability to follow instructions (S11) Concentration—attention to detail (S12) Critical thinking (S13)

The primary objective of this study is to develop a hybrid model for Taiwan's manufacturing industry to assess workforce recruitment factors and aid in decision-making. The results, displayed in Tables 16 and 17, show the weighted criteria and sub-criteria, highlighting the most critical factors. This model helps organizations optimize resource allocation, saving time and money during recruitment.

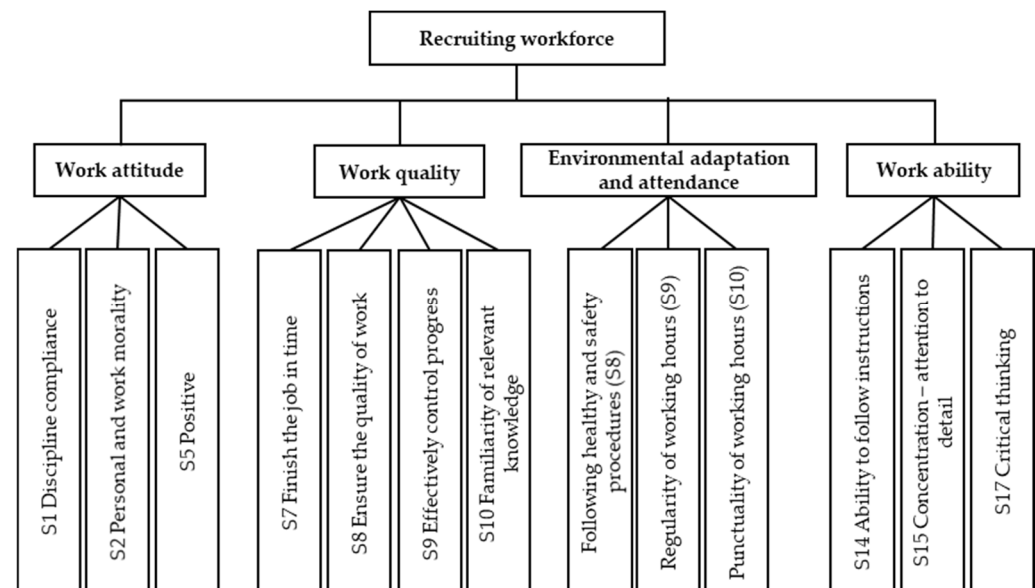
Table 16. The overall weight ranking table of criteria (FANP).

Criteria	Criteria Ranking
C1 Work attitude	1
C3 Environmental adaption and attendance	2
C4 Work ability	3
C2 Work quality	4

Table 17. The overall weight ranking table of sub-criteria (FANP).

Sub-Criteria	Sub-Criteria Ranking
S1 Discipline compliance	1
S3 Positive	2
S8 Following healthy and safety procedures	3
S2 Personal and work morality	4
S11 Ability to follow instructions	5
S9 Regularity of working hours	6
S12 Concentration—attention to detail	7
S10 Punctuality of working hours	8
S13 Critical Thinking	9
S5 Ensure the quality of work	10
S6 Effectively control progress	11
S7 Familiar with relevant knowledge	12
S4 Finish the job in time	13

This study's approach offers advantages over traditional recruiting methods in Taiwan's electronics manufacturing industry. Conventional methods focus on qualifications, availability, salary expectations, culture, and experience, often leading to less informed decisions. In contrast, this study uses advanced techniques to identify critical workforce selection criteria. The FDM synthesizes expert opinions, eliminates the less important criteria and sub-criteria, and retains the essential ones. The remaining critical criteria consist of 4 main criteria and 13 sub-criteria (Table 15). A hierarchical structure (Figure 5) was then constructed based on these critical criteria to assist Taiwan's electronics manufacturing companies in evaluating the workforce recruitment process. ISM uncovers relationships between criteria, and FANP prioritizes these criteria considering uncertainties and complexities. This tailored approach addresses Taiwan's unique challenges, such as labor shortages, an aging population, and rapid technological changes, providing targeted solutions for improved recruitment and retention.

**Figure 5.** The hierarchical structure for workforce recruitment.

Taiwan's electronics manufacturing industry prioritizes Work Attitude (C1) like willingness to work night shifts, overtime cooperation, discipline, flexibility, and a positive attitude. These traits are crucial for maintaining a harmonious and adaptable workforce in a high-pressure, rapidly evolving environment. Human Resources (HR) should assess these traits during recruitment through methods like behavioral interviews, reference checks,

and personality assessments. Other manufacturing sectors, especially in Western countries, often prioritize technical skills, overlooking the benefits of a positive work attitude.

The second crucial criterion, Environmental Adaptation and Attendance (C4) highlights the significance of employees' capacity to uphold an orderly work environment, maintain consistent attendance, respect cultural diversity, adhere to health and safety protocols, and possess pertinent knowledge. Other manufacturing industries might not prioritize environmental adaptation and attendance to the same extent. For example, industries with more predictable and stable work environments may focus less on these factors and more on specific technical skills or experience. Recruitment strategies should include assessments of candidates' organizational skills, quality control capabilities, and relevant knowledge.

Work Ability, the third most critical aspect, emphasizes practical and technical skills such as operating machinery, attention to detail, experience, education, critical thinking, and basic computer skills. These skills are essential for effective job performance and technical tasks within the manufacturing environment. Recruitment should, therefore, include technical assessments, practical tests, and evaluations of educational background and experience. While technical skills remain important, the study highlights the need to balance these with soft skills and adaptability. This can lead to hiring technically proficient employees who might struggle with adaptability or teamwork.

Drawing from the research findings mentioned above, the following recommendations regarding decision factors for recruiting a workforce can serve as a reference for the HR department and hiring supervisors within a manufacturing unit:

Human resources department

1. Advance Manpower Planning

HR should understand recruitment schedules for different personnel categories. For high-demand roles like skilled production line workers, starting recruitment six months in advance reduces hiring time and improves workforce stability. This proactive approach also prevents manpower shortages during peak production periods. For long-term, steady workforce needs, partnering with educational institutions and planning recruitment one to three years ahead is crucial. Anticipating recruitment needs ensures a steady supply of qualified candidates, avoids last-minute hiring pressures, and aligns workforce availability with production demands. This strategy enhances operational efficiency and reduces downtime, unlike traditional short-term recruitment efforts that often lead to staffing shortages and increased operational downtime.

2. Align Staffing with Capacity Cycles

The electronics manufacturing sector often faces shifts due to changes in consumer demand, causing production capacity fluctuations. Urgent orders make it impractical to rely solely on regular staff, foreign workers, or industry-academic graduates. In such cases, engaging temporary personnel through short-term training programs is a viable solution. A proactive approach involves analyzing manpower needs, identifying peak seasons, and planning for flexible workforce adjustments. This strategy stabilizes staffing, maintains product quality during demand surges, and enhances the company's reputation while offering temporary job opportunities. Conventional staffing methods often fail to manage rapid shifts, leading to overstaffing or understaffing, which negatively affects production efficiency and employee morale.

Manufacturing facilities

1. Evaluate Job Compatibility

The manufacturing unit supervisor can optimize job assignments by considering the distinct characteristics of various personnel types. For instance, if foreign workers prefer night shifts or are more willing to collaborate on machinery operations, managers can allocate these tasks accordingly. The study found that assigning tasks based on personal preferences and strengths, such as giving more night shifts or machinery operation tasks to foreign workers who prefer these roles, increased job satisfaction and productivity.

Tailoring job assignments to match worker characteristics optimizes performance and enhances employee retention, ensuring employees are more engaged and productive in their roles. Traditional methods often overlook individual worker preferences, leading to mismatched job assignments that can decrease productivity and increase turnover.

2. Optimize Workforce Allocation

The manufacturing unit supervisor can optimize production line efficiency by categorizing stations based on personnel attributes and planning deployment accordingly. Long-term, simple tasks can be assigned to students, short-term, low-skill roles to contingency staff, and night shifts to foreign personnel through early HR requests. This strategy improves task efficiency and job satisfaction by matching roles with worker strengths, ensuring smooth operations and timely staffing. In contrast, standard workforce allocation often uses a one-size-fits-all approach, leading to suboptimal performance.

6. Conclusions and Recommendations

Selecting the most suitable strategies for recruiting a workforce is complex, often involving conflicting criteria. Many manufacturing firms use decision-making models to address these challenges, but existing models often fall short, leading to poor decisions with unpredictable consequences. An effective decision-making model for recruitment can mitigate risks and improve candidate selection. This study proposes an integrated decision-making model for talent acquisition using a multifaceted approach: literature review and expert panel analysis, FDM, ISM, and FANP. Implementing these approaches in a Taiwanese manufacturing firm revealed four essential evaluation criteria and thirteen sub-criteria for workforce selection, each with their respective weightings. The research highlights the importance of three primary criteria: C1 (Work Attitude), C3 (Environmental Adaptation and Attendance), and C4 (Work Ability). The top sub-criteria identified are S1 (Discipline Compliance), S3 (Positive Attitude), and S8 (Following Health and Safety Procedures). These findings suggest that manufacturing enterprises should prioritize candidates with excellent work attitudes and environmental adaptability, emphasizing discipline compliance to save time and costs while improving workforce quality.

This study contributes in three key ways. Firstly, it develops a systematic technique for selecting criteria through a comprehensive literature review and expert interviews. The FDM is used to retain the most critical criteria while eliminating less important ones, ensuring a focus on the most important factors. Secondly, it establishes and measures relationships among decision criteria for workforce selection using the ISM approach. This provides decision-makers in Taiwan's electronics manufacturing sector with consistent criteria relations. Thirdly, it proposes an application model using the FANP method to identify and prioritize the most suitable criteria for personnel recruitment. No previous study has combined these three methods to determine the most important criteria for workforce selection in Taiwan's electronics manufacturing industry in the context of a labor shortage. This research enriches the repertoire of references available for decision-making models in the context of talent recruitment and the broader field of manufacturing. It contributes to the ongoing body of knowledge in these domains, offering insights and methodologies that can inform and enhance decision-making processes in workforce recruitment and management.

This study acknowledges three limitations. Firstly, there may be variations in the selected criteria and sub-criteria as well as the expert assessments concerning the significance of pairwise criteria among different members of the expert panel. Future research could address this by incorporating a larger and more diverse pool of expert opinions from the beginning, ensuring a broader perspective and enhancing the robustness and applicability of the decision-making model. Secondly, the scope of this research is confined to the Taiwan manufacturing industry. Consequently, the model developed for talent recruitment is context-specific and may serve as a reference or guideline for manufacturing enterprises in other countries but cannot be directly applied due to potential contextual disparities. Future research could broaden the scope to include diverse industries and coun-

tries, enabling the development of a more universally applicable talent recruitment model. Thirdly, the current study focuses primarily on the general labor force; future research could expand the proposed decision-making framework to diverse workforce categories, examining their distinctive characteristics and alignment with manufacturing operations. This would provide a more comprehensive understanding of talent recruitment's impact on firm productivity across different labor forces.

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