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An Integrated Fuzzy DEMATEL and Fuzzy TOPSIS Method for Analyzing Smart Manufacturing Technologies

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Abstract: I4.0 promotes a future in which highly individualized goods are mass produced at a competitive price through autonomous, responsive manufacturing. In order to attain market competitiveness, organizations require proper integration of I4.0 technologies and manufacturing strategy outputs (MSOs). Implementing such a comprehensive integration relies on carefully selecting I4.0 technologies to meet industrial requirements. There is little clarity on the impact of I4.0 technologies on MSOs, and the literature provides little attention to this topic. This research investigates the influence of I4.0 technologies on MSOs by combining reliable MCDM methods. This research uses a combination of fuzzy DEMATEL and fuzzy TOPSIS to evaluate the impact of I4.0 technologies on MSOs. The fuzzy theory is implemented in DEMATEL and TOPSIS to deal with the uncertainty and vagueness of human judgment. The FDEMATEL was utilized to identify interrelationships and determine criterion a's weights, while the fuzzy TOPSIS approach was employed to rank the I4.0 technologies. According to the study's findings, cost is the most critical factor determining MSOs' market competitiveness, followed by flexibility and performance. On the other hand, additive manufacturing (AM) is the best I4.0 technology for competing in the global market. The results present an evaluation model for analyzing the relative important weight of multiple factors on MSOs. They can also assist managers in concentrating on the most influential factors and selecting the proper I4.0 Technology to preserve competitiveness.

Keywords: industry 4.0; digitalization; manufacturing strategies; MCDM; fuzzy DEMATEL; fuzzy TOPSIS

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1. Introduction

Today's manufacturers are challenged with an ever-increasing demand for product diversity and unpredictable market requirements. In order to keep up with the ever-changing market, boost product quality, and maximize efficiency, manufacturers must embrace novel techniques [1]. There has recently been a collaboration between international organizations in order to develop the smart manufacturing [2]; with enhanced technology for sensing, and decision-making, autonomous manufacturing activities can be performed to meet customer demands [3]. Smart manufacturing uses product lifetime data to improve all aspects of manufacturing. Hence, I4.0 is a breakthrough wave that meets customer needs efficiently. Designers describe this "flexible integration of the global value chain"—making customer-requested products efficient [4,5]. Its goal is to create cost-effective, flexible workflows that deliver high-quality, personalized products at low unit costs.

Cost-efficient, intelligent, effective, customized, and configurable products are possible with I4.0. Automation and data exchange help I4.0 digitalize manufacturing [6]. Cyber-physical systems (CPS) are emphasized for their potential to integrate machines, factories, and business processes and for their distinctive features, such as autonomous information sharing, activity triggering, decision-making, and independent control [7]. With CPS and the IoT, intelligent devices are constantly interacting and communicating with one another, bridging the gap between the digital/virtual and real/physical worlds [8]. I4.0 improves industrial capability by making it easier to produce the appropriate products of the best quality, with fast delivery, at a low price, while keeping the environment safe [9]. It is feasible to make things and machines smarter by enabling them to connect with and learn from one another thanks to quicker computers, intelligent devices, and more inexpensive [10].

A manufacturing strategy (MS) is a long-term plan for using the resources of the manufacturing system to achieve the company's goals [11]. A manufacturing strategy is an approach to production that aims to maximize performance while striking a balance between different performance objectives. All manufacturing policies should be developed in tandem with or in support of the company strategy, which should be a priority for the highest levels of management [12]. These days, a company's manufacturing capabilities are one of its most distinguishing features in the marketplace [13]. Therefore, businesses must develop their production plans. To increase manufacturing production, it is necessary to establish a connection between manufacturing goals and business goals [14]. In order to increase output and performance as a whole, I4.0 and MSOs need to be properly aligned.

To help businesses compete in today's global economy, this research developed a hybrid MCDM model for ranking I4.0 technologies. FDEMATEL analyzes the interrelationships and feedback between the criteria under uncertainty and calculates weights. Thus, FTOPSIS is used to rank the I4.0 technologies. It is widely known that the conventional production system cannot preserve the business's competitive edge due to insufficient and predetermined assets, fixed routes, a lack of communication, autonomous management, and fragmented data. Business is faced with new challenges caused by globalization, including a more complex and competitive market, trading environments, and unpredictable and hazardous. In order to maintain a competitive edge, businesses must invest in I4.0 technologies that affect MSOs. Deep digitalization integration with the broader economy has emerged as a crucial method for enhancing industrial production's competitiveness and quality growth [15,16]. The research contributes to identifying and classifying MSOs relevant to I4.0 technologies through a review of pertinent literature and the opinions of experts in the field. The proposed method investigated the effects of I4.0 technologies on MSOs, allowing managers to make more informed decisions and enhance their market competitiveness.

The outline of this study is as follows: The literature review is addressed in Section 2. In Section 3, the authors discuss the methodology. Section 4 presents the findings and discusses them. Discussion of implications in Section 5. Finally, the conclusion and future study are provided.

2. Literature Review

Smart manufacturing, defined as I4.0′s key pillar, incorporates various technologies and digitally changes businesses to reach market competency, as shown in Figure 1. The manufacturing and development of new items have become increasingly complex and complicated. While there are numerous modifications and differences in customer needs, the system must be highly flexible to create various products on a similar system [17]. In the twenty-first century, manufacturers face new challenges brought on by globalization, such as unexpected market shifts. The new emerging production paradigm is called personalization or personalized production, and it is motivated by consumers' desire to have input into and ownership over product design [18]. A dedicated production line, a flexible manufacturing system, and a reconfigurable manufacturing system are all parts of the industry 4.0 production system [19]. In order to boost overall production and performance, I4.0 and MSOs need to be properly aligned. According to the reported studies [14,20–27], the I4.0 technologies are shown in Figure 2 and described in our previously published paper [25].

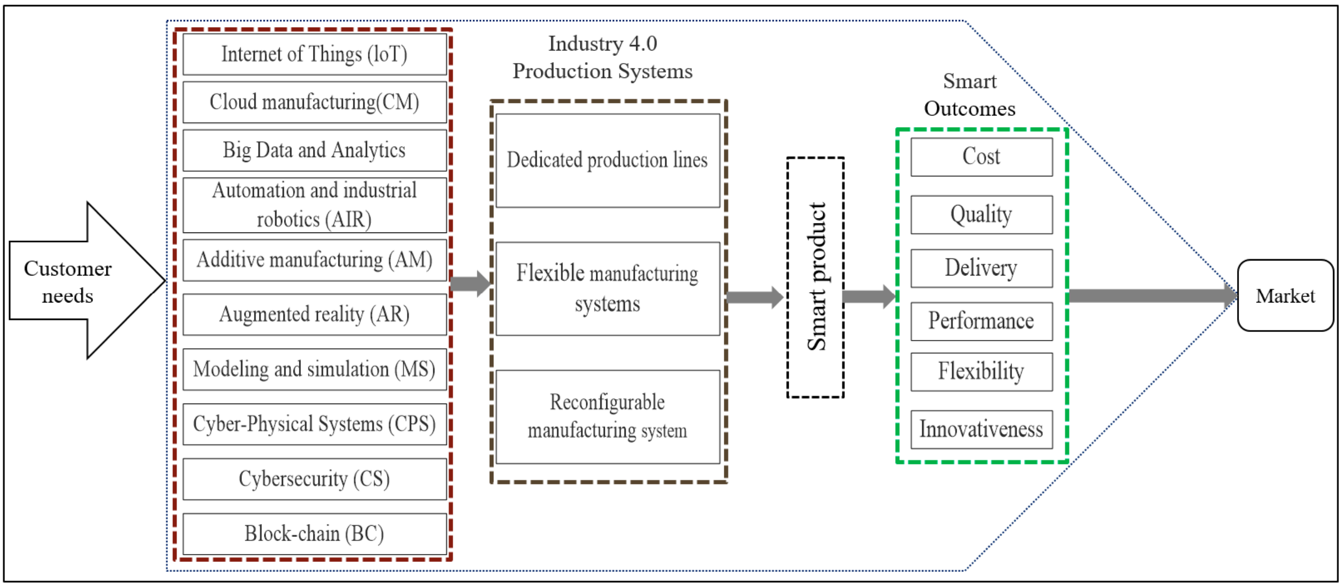

Figure 1. Smart manufacturing framework.

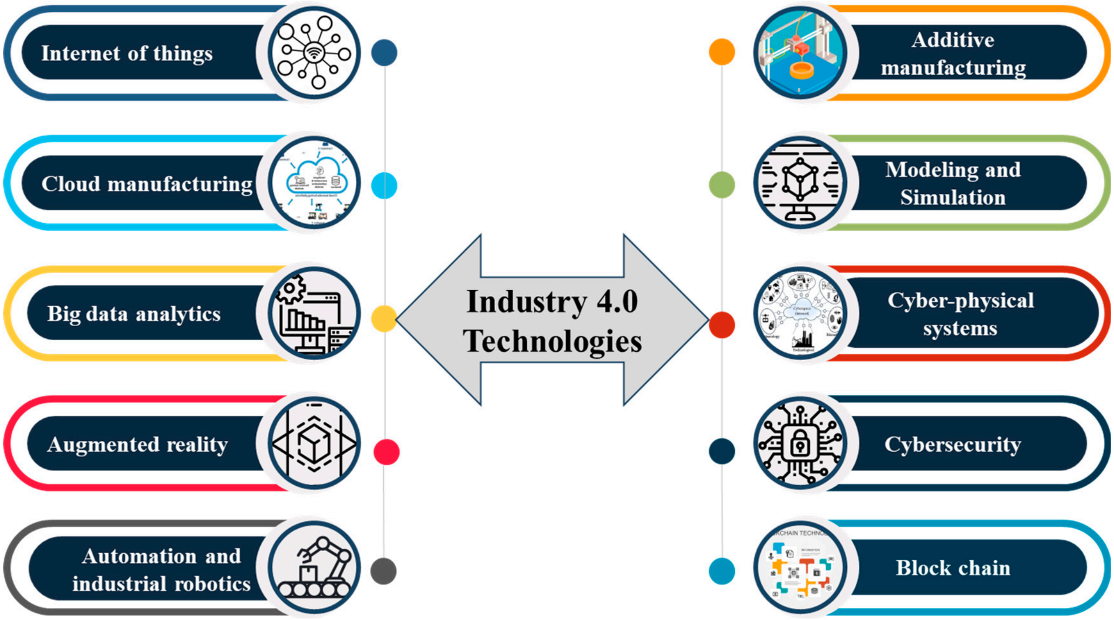

Figure 2. Industry 4.0 Technologies.

An organization's manufacturing strategy is its long-term plan for employing its manufacturing system's resources in service of its overarching business strategy and achieving its objectives [11]. It is also known as a framework aims to improve a business's ability to compete in its industry by ensuring its manufacturing resources are designed, managed, and developed to provide a balanced set of performance characteristics [28]. Manufacturing strategies assist businesses in developing a well-organized manufacturing structure [29]. A manufacturing firm's productivity and ability to distinguish itself from the competition are both improved by a well-organized structure. Strategically, it becomes a factor in the competition for such businesses, as it helps them differentiate themselves from their competitors [13]. In the literature, MSOs are also known as competitive priorities [23,30]. Competitive priorities motivate the entire company to gain an advantage over its rivals. The description of MSOs is shown in Table 1.

Table 1. Manufacturing strategies outputs [23,30].

Criteria	Description
Cost	Maintaining market-competitive rates while reducing total costs.
Quality	Maintaining a high degree of customer satisfaction while establishing and maintaining rigorous standards, quality control, and management procedures.
Delivery	The time between receiving an order and delivering it to the customer.
Flexibility	Ability to offer customized products and services and raise or reduce the number of existing products to respond quickly to customer demands.
Performance	Product features and their ability to achieve things other products cannot.
Innovativeness	Quickly introducing new products or redesigning current ones.

Numerous studies have clarified the significance of integrating I4.0 technologies to improve MSOs. May and Kiritsis [31] used I4.0 technologies to achieve error-free assembly lines, boosting productivity, quality, customer satisfaction, profitability, and long-term viability in the manufacturing sector. Tortorella and Fettermann [32] employed I4.0 technologies, including big data, IoT, etc., to boost MSOs quality and performance. Ghobakhloo [21] built a balancing framework serves as a jumping-off point for researchers and industry professionals to develop a comprehensive strategy for an easy transition from traditional manufacturing to I4.0, resulting in improved performance across the board. Ghobakhloo and Fathi [33] utilized I4.0 technologies to demonstrate how SME manufacturers may optimize their information technology investment to create lean, digitalized production procedures that boost their long-term competitiveness and performance. Tortorella and Giglio et al. [34] used I4.0 technologies to increase operational efficiency in Brazil's lean production (LP) system.

As the manufacturing process becomes more complex, manufacturers are greatly concerned about making good decisions. Therefore, in a fuzzy environment, MCDM techniques can significantly decrease the problem's complexity [35–37]. Commonly, researchers use the DEMATEL to determine if there is a link between the variables. This approach assists in creating a structural model to analyze how various factors interact in extended and comprehensive studies [38]. These factors are graded based on the type of relationship they reflect and the degree of their interdependence. This method uses matrices to convert interdependencies into a group of causes and effects and impact relationship diagrams to identify the influential factors of a complex structural system. DEMATEL can help identify real solutions, specific problems, clusters of complex issues, and weight calculations based on interdependencies [39,40].

DEMATEL demonstrates graphically and statistically the relevance and intensity of relationships [41]. It represents and quantifies the degree to which complex system elements are interdependent [42]. Crisp values frequently indicate human judgments for determining the interaction between components when DEMATEL is applied. In contrast, in the real world, exact values are often inadequate [43]. Fuzzy logic is necessary because people's preferences are typically ambiguous and difficult to quantify with precise numbers. This research employs fuzzy set theory and the DEMATEL technique to build a structural model of the interaction between several criteria [44]. In 1965, Lotfi A. Zadeh established the discipline of fuzzy logic to examine the ways in which humans deal with ambiguity and uncertainty when making decisions. Several judgements are brought on by limits and ambiguous, uncertain events, as is evident from an evaluation of decision-making issues in real-world transactions [45]. It is argued that converting linguistic notions into fuzzily defined numbers is better than combining distinct individual or group perspectives, conceptions, or judgments. The fuzzy DEMATEL method necessitates the construction of a causality map, as well as the gathering of impact and causality indicators for each factor. The technique creates the causal diagram and categorizes factors based on their distances from the element's center and their degrees of cause and effect (into cause groups or effect groups). In the end, it presents several suggestions for further research and managerial implications. Last but not least, it highlights key elements that facilitate more effective problem-solving [46].

The TOPSIS ranking approach is well-known for its ability to rank alternatives in descending order of importance. According to TOPSIS, the optimal decision is the one that is most similar to the optimal positive solution and most different from the optimal negative solution. As a result, the optimal solution is one that maximizes benefits while minimizing costs. This means the worst possible values for each criterion may be found in the negative ideal solution, while the best possible values can be found in the perfect solution [47]. One of TOPSIS's main advantages is that it ranks alternatives by their influence using unlimited data for each indication [48]. Dos Santos et al. [49] proposed that TOPSIS be used with other MCDM methods to provide more efficient and flexible problem-solving. MCDM methods have been used more frequently in recent research, individually or in combination with other MCDM approaches. In recent studies, hybridizations of MCDM approaches, such as DEMATEL and TOPSIS, have been observed [50–54]: DEMATEL, TOPSIS, ANP [55–57], AHP-BWM [58], and DEMATEL, AHP and TOPSIS [59–61]. The literature review revealed that no prior studies had presented a hybrid integrated fuzzy DEMATEL-TOPSIS to investigate how I4.0 technologies can affect MSOs.

3. Research Methodology

This section demonstrates a hybrid MCDM method to help decision makers evaluate and rank the impact of I4.0 technologies on MSOs. Figure 3 shows the I4.0 technologies and MSOs evaluation network. This study's experts were chosen according to their expertise and experience [62]. According to [63], The minimum required of experience for an acceptable expert is ten years, either in academia, industry, or both. The majority of the selected manufacturing firms were active participants in I4.0. Research participants include top-level executives, general managers, department heads, specialist engineers, academics, and professionals working in manufacturing strategies related to industrial organizations, with an emphasis on MSOs. Specialists need in-depth knowledge of the manufacturing process, focusing on smart manufacturing techniques.

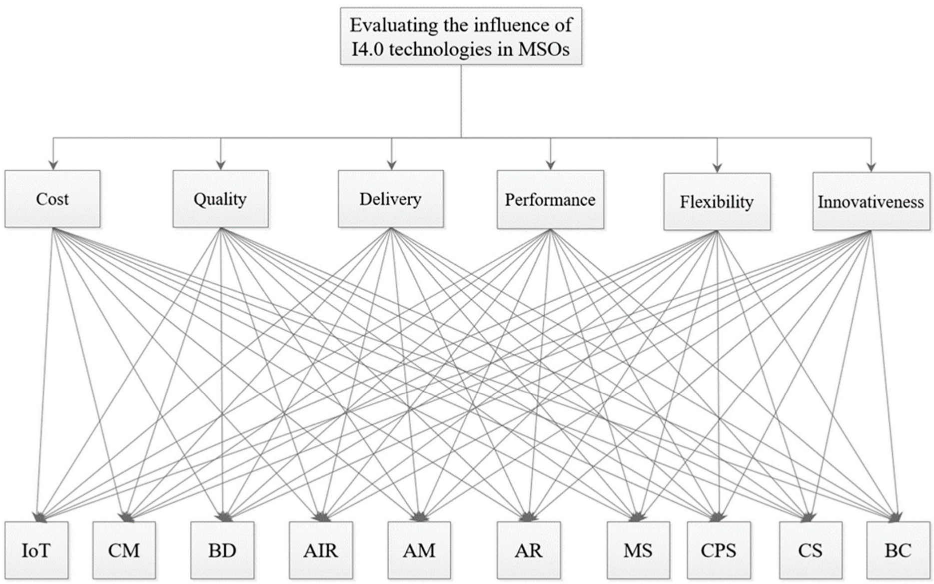

Figure 3. I4.0 technologies on MSOs evaluation network.

Experts are also expected to have experience with I4.0 technologies, either from a theoretical or practical perspective. Their responsibilities may have included market strategy and operations. As a result, they have a deep understanding of production methods. Experts in the field of academia were similarly selected among professors and PhDs, who have contributed to scholarly journals with works on industry 4.0.

A personal interview was conducted with an expert explaining the research and an online interview with those unable to attend in person. Initial participants were contacted via email to confirm their participation and explain the study's goals. Most experts responded positively. Unfortunately, only 14 of the planned professional respondents filled out the surveys in their entirety. Therefore, the selected academic experts significantly contributed significantly to this sector.

Proposed Model

In order to attain market competitiveness, a hybrid MCDM for ranking I4.0 technologies is developed. It can be accomplished using the following phases.

Phase 1. Constricting the MCDM model

Figure 4 illustrates the phases of the evaluation model designed for the impact of I4.0 technologies on MSOs' evaluation networks. In the first phase, researchers reviewed the literature related to this topic and documented their findings; we focused on the I4.0 concept and its associated technologies and manufacturing strategies. We reviewed past works on I4.0 technologies and conducted interviews with experts. With the experts' agreement, a primary network was established. The evaluation's scope was determined and then a framework was built for this network.

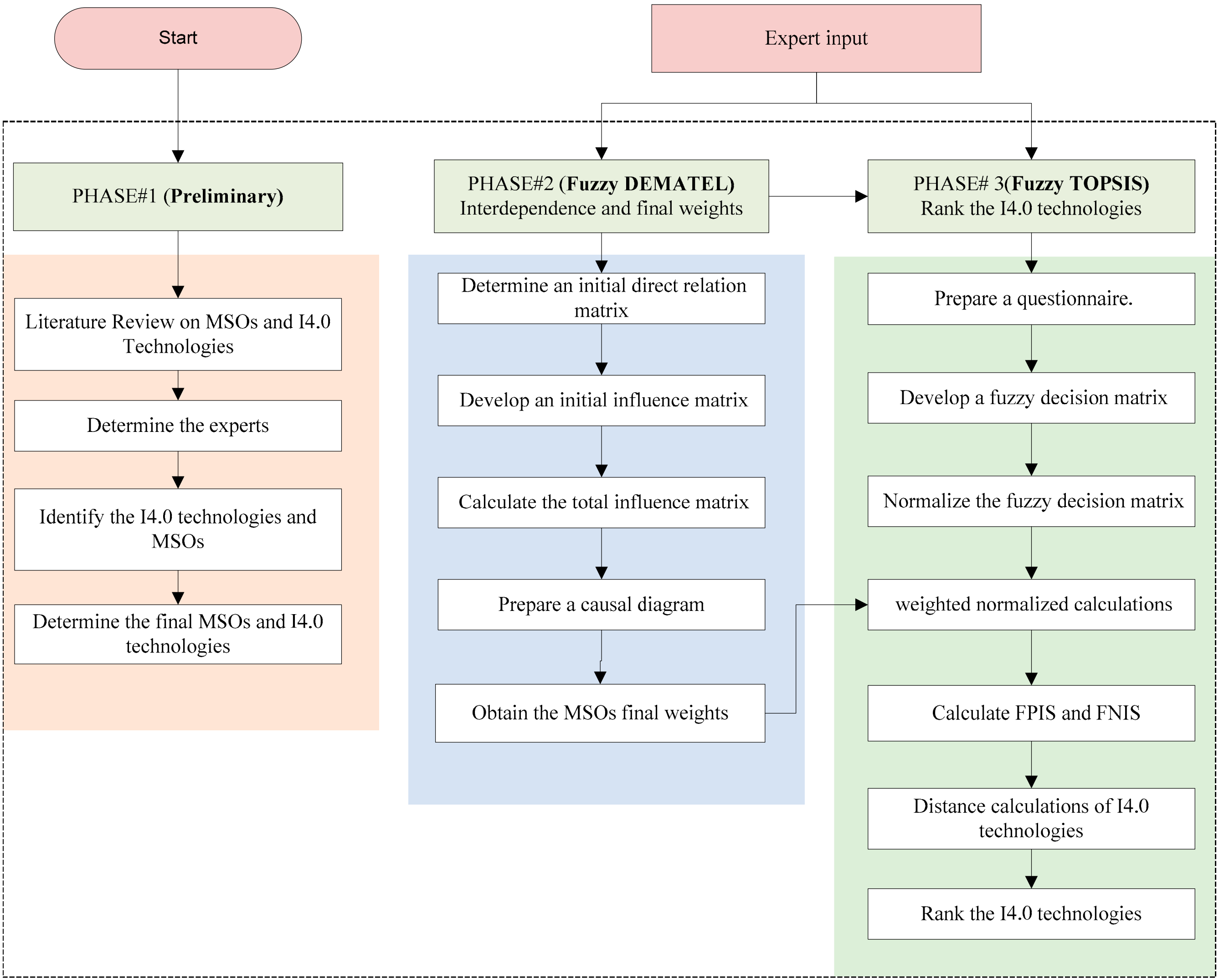

Figure 4. A hybrid MCDM evaluation model.

Phase 2. Fuzzy DEMATEL Method

Several types of research have effectively used the DEMATEL method to evaluate the factors about knowledge and expert practices in the context of MCDM issues. The FDEMATEL was used to find interrelationships and establish the weights for criteria. The three numbers (l, m, r) represent a triangular fuzzy number, l for the most pessimistic, and r for the most optimistic. Equation (2) explains the triangle fuzzy number membership function.

$$Z^k = \begin{array}{c} C_1 \\ C_2 \\ \vdots \\ C_n \end{array} \begin{bmatrix} [0,0,0] & x^k{}_{12} & \cdots & x^k{}_{1n} \\ x^k{}_{21} & [0,0,0] & \cdots & x^k{}_{2n} \\ \vdots\ \vdots & & \vdots & \vdots \\ x^k{}_{n1} & x^k{}_{n2} & \cdots & [0,0,0] \end{bmatrix} \tag{1}$$

$$\mu_N\ (x) = \begin{cases} 0, & x < l \\ \frac{x-l}{m-l}, & l \le x \le m \\ \frac{r-x}{l-m}, & m \le x \le r \\ 0, & x > r \end{cases} \tag{2}$$

where l represents the fuzzy left score, r is the fuzzy right score, and m is the fuzzy center score of the triangle. The steps of the fuzzy DEMATEL approach are as follows [27,54,55]:

Step 1. Create a fuzzy scale, decision goals, and criteria (C, Q, D, F, P I);

Step 2. Choose experts with relevant knowledge and experience to compare pairwise effects;

Step 3. Create a semantic evaluation form that categorizes the degree of influence between various factors into the five categories listed in Table 2. The form needs to be simple to read and understand;

Table 2. Fuzzy triangular numbers used in FDEMATEL [24,64].

Linguistic Terms	Symbol	Fuzzy Triangular Numbers
No impact	NO	(0.00,0.10,0.30)
Very low impact	VL	(0.10,0.30,0.50)
Low impact	L	(0.30,0.50,0.70)
High impact	H	(0.50,0.70,0.90)
Very high impact	VH	(0.70,0.90,1.00)

Step 4. Obtain the initial direct influence matrix. The interpretation of the semantic assessment table by experts should be used to generate a direct effect matrix;

Step 5. In order to account for uncertainty in human judgments, convert the direct impact from step three into fuzzy triangular values, as shown in Table 2;

Step 6. Create fuzzy direct-relation matrices Z^K by having evaluators create fuzzy pairwise impact correlations between components in a $n\ x\ n$ matrix, where k is the number of experts;

Step 7. Once the numbers are defuzzed using the CSCF method, the overall score can be determined by taking the weighted average of the left and right scores of the membership function. This approach is the most effective in the literature for producing consistent outcomes [65,66]. The CFCS method determines the maximum and minimum fuzzy values within a fuzzy number range. The overall score is defined as a weighted average based on membership functions. Each population score results in a fresh beginning influence matrix. Listed below are the detailed procedures:

Normalize the fuzzy triangular numbers, where $0 \le x_{ij} \le 1$:

$$xl^k{}_{ij} = \frac{l^k{}_{ij} - minl^k{}_{ij}}{\Delta_{min}^{max}} \tag{3}$$

$$xm^{k}{}_{ij}=\frac{m^{k}{}_{ij}-minl^{k}{}_{ij}}{\Delta_{min}^{max}} \quad (4)$$

$$xr^{k}{}_{ij}=\frac{r^{k}{}_{ij}-minl^{k}{}_{ij}}{\Delta_{min}^{max}} \quad (5)$$

$$\Delta_{min}^{max}= maxr^{k}{}_{ij}-minl^{k}{}_{ij} \quad (6)$$

Calculate the left and right normalized scores:

$$xls^{k}{}_{ij}=\frac{xm^{k}{}_{ij}}{\left(1+xm^{k}{}_{ij}-xl^{k}{}_{ij}\right)} \quad (7)$$

$$xrs^{k}{}_{ij}=\frac{xr^{k}{}_{ij}}{\left(1+xr^{k}{}_{ij}-xm^{k}{}_{ij}\right)} \quad (8)$$

Obtain the crisp values:

$$x^{k}{}_{ij}=\frac{xls^{k}{}_{ij}*\left(1-xls^{k}{}_{ij}\right)+xrs^{k}{}_{ij}*xrs^{k}{}_{ij}}{\left(1-xl^{k}{}_{ij}+xrs^{k}{}_{ij}\right)} \quad (9)$$

Create the total normalized crisp values of the expert, k:

$$z^{k}{}_{ij}=minl^{k}{}_{ij}+x^{k}{}_{ij}*\Delta_{min}^{max} \quad (10)$$

Collect the crisp normalized values for each factor to construct the direct relationship matrix:

$$z_{ij}=\frac{Z^{1}{}_{ij}+Z^{2}{}_{ij}+\cdots+Z^{n}{}_{ij}}{n} \quad (11)$$

The initial direct influence matrix is utilized to generate a standardized direct influence matrix, where $X=\left[x_{ij}\right]_{n*n}$, and $0\leq x_{ij}\leq 1$. The calculation is as follows:

$$X=s*Z \quad (12)$$

$$s=\frac{1}{\max\limits_{1\leq i\leq n}\sum_{j=n}^{m}z_{ij}},i,j=1,2,\ldots,\ n. \quad (13)$$

Compute the influence matrix $T=\left[t_{ij}\right]_{n*n}$. The factors t_{ij} display the indirect influence between factors i and j. The influence matrix T reflects the entirety of the impact relationship between items. The matrix is computed as follows:

$$T=\lim_{m\to\infty}\left(X+\quad X^{2}+\quad X^{3}\quad\ldots\quad X^{m}\quad\right)=X^{*}(1-X)^{-1} \quad (14)$$

Using the following formulas, calculate the degree of each factor's influence, influenced, center, and cause degree: D_i Represents the degree to which one factor influences another factor in MSOs.

$$\text{The influence degree}:\ D_i=\sum_{j=1}^{n}t_{ij} \quad (15)$$

The affected degree R_j: How much one factor affects another among a set of MSOs.

$$\text{The affected degree}:\ R_j=\sum_{i=1}^{n}t_{ij} \quad (16)$$

The center degree $\left(R_j-D_i\right)$, indicates the relative importance of factors within the MSOs.

$$The\ center\ degree=\left\{\left(R_j+D_i\right)\middle|i=j\right\} \quad (17)$$

For the cause degree,
When $R_j + D_i$ Is positive, the factor belongs to the cause group.
When $R_j - D_i$ is negative, the factor belongs to the effect group.

$$\text{The cause degree} = \{(R_j - D_i)|i = j\} \tag{18}$$

Step 8. Estimate the relative weights of each criterion by using Equation (19).

$$w_i = \frac{R_j + D_i}{\sum_{i=1}^{n} R_j + D_i} \tag{19}$$

Fuzzy TOPSIS method

Chen [67] created the fuzzy TOPSIS method for solving uncertain MCDM problems. Decision makers $D_r(r = 1, \ldots, k)$ estimate criteria weights and alternative evaluations using linguistic data. Thus, ${W_r}^j$ represents the importance of the jth criterion, C_j (j = 1, . . . , m), outlined by the rth decision maker. Similarly, ${W_r}^j$ represents the score of the ith I4.0 technology (alternatives), A_i (i = 1, 2, . . . , n), regarding criterion j, as indicated by the rth decider. The fuzzy triangular numbers required by fuzzy TOPSIS are presented in Table 3. Under these assumptions, the procedure includes the following [68–70]:

Table 3. Fuzzy TOPSIS scale.

The Extent of the Influence	Fuzzy Triangular Number
Very high impact (VH)	7.00 9.00 9.00
High impact (H)	5.00 7.00 9.00
Medium impact (M)	3.00 5.00 7.00
Low impact (L)	1.00 3.00 5.00
Very Low impact (VL)	1.00 1.00 3.00

Step 1. As shown by Equations (20) and (21), aggregate the relative significances and evaluations of alternatives provided by k decision makers.

$$W_j = \frac{1}{k}\left[W_j^1 + W_j^2 + \cdots + W_j^k\right] \tag{20}$$

$$x_j = \frac{1}{k}\left[x_j^1 + x_j^2 + \cdots + x_j^k\right] \tag{21}$$

Step 2. Use Equations (22) and (23) to combine the criteria and alternatives in the fuzzy decision matrix (W).

$$D = \begin{bmatrix} \cdot & \cdot & \cdots & \cdot \\ \mathrm{x}_{11} & \mathrm{x}_{12} & \cdots & \mathrm{x}_{1\mathrm{m}} \\ \vdots & \vdots & \vdots & \vdots \\ \mathrm{x}_{\mathrm{n}1} & \mathrm{x}_{\mathrm{n}2} & \cdots & \mathrm{x}_{\mathrm{nm}} \end{bmatrix} \tag{22}$$

$$W_j = [W_1 + W_2 + \cdots + W_m] \tag{23}$$

Step 3. The fuzzy decision matrix can be normalized via a linear-scale transformation (D). The Equations (24)–(26) provide the normalized fuzzy decision matrix R.

$$R = [r_{ij}]_{m\ X\ n} \tag{24}$$

$$r_{ij} = \left(\frac{l_{ij}}{u_j^+}, \frac{m_{ij}}{u_j^+}, \frac{u_{ij}}{u_j^+}\right) \text{ and } u_j^+ = \ max_i\ u_{ij}(\text{benefit criteria}) \tag{25}$$

$$r_{ij} = \left(\frac{l_j^-}{u_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}} \right) \text{ and } l_j^- = max_i \, l_{ij} (\cos \text{t criteria}) \tag{26}$$

Step 4. Multiply the relative importance of each criterion results to the weighted normalized decision matrix V, W_j, according to the factors of the normalized fuzzy decision matrix, r_{ij}, as shown in the following Equation (27).

$$V = [v_{ij}]_{m \times n} \tag{27}$$

where v_{ij} is provided by Equation (28).

$$v_{ij} = x_{ij} \times w_{ij} \tag{28}$$

Step 5. Determine the fuzzy positive ideal solution (FPIS, A^+) and fuzzy negative ideal solution (FNIS, A^-) using Equations (29) and (30).

$$A^+ = \left\{ v_1^+, v_j^+, \ldots, v_m^+ \right\} \tag{29}$$

$$A^- = \left\{ v_1^-, v_j^-, \ldots, v_m^- \right\} \tag{30}$$

Step 6. Compute the distances ${d_j}^+$ and ${d_j}^-$ with equations for each possible option (31) and (32).

$${d_j}^+ = \sum_{j=1}^n d_v \left(v_{ij}, v_j^+ \right) \tag{31}$$

$${d_j}^- = \sum_{j=1}^n d_v \left(v_{ij}, v_j^- \right) \tag{32}$$

where d is the vertex-based distance between two fuzzy values. This can be demonstrated using the Equation (33).

$$d(x,z) = \sqrt{\frac{1}{3} \left[(l_x - l_z)^2 + (m - m_z)^2 + (u_x - u_z)^2 \right]} \tag{33}$$

Step 7. Applying Equation (34), determine the closeness coefficient CC_i.

$$CC_i = \frac{{d_j}^+}{{d_j}^+ + {d_j}^-} \tag{34}$$

Step 8. Determine the decreasing order of the alternatives based on the closeness coefficient, CC_i. The optimal option is the one that is closest to the FPIS and farthest from the FNIS.

4. Results and Discussions

4.1. FDEMATEL Calculations

Experts were provided a questionnaire to determine how each pair of criteria related. "How much influence does each component on the left has on the factor on the right?" was asked for each option. As shown in Table 2, respondents rated their level of satisfaction on a scale from one to five. Table 4 displays the fuzzy triangular numbers of a single expert generated by translating linguistic data to a fuzzy linguistic scale based on the results from the experts. Based on the fuzzy evaluation, the original direct relation matrix is used to compute the crisp value of MSO criteria. As indicated in Table 5, the total relation matrix can be obtained. The impact relation among factors is shown in Table 6. The final results of the DEMATEL analysis are obtained, as shown in Table 7. Figure 5 illustrates the interdependence and relationship of MSOs. As shown in Table 7, the six outputs can be categorized by their respective causes and effects, and previous studies support this finding [26].

Table 4. Fuzzy direct-influence matrix.

MSOs	C			Q			D			F			P			I		
C	1	1	1	0.5	0.7	0.9	0.5	0.7	0.9	0.1	0.3	0.5	0.3	0.5	0.7	0.5	0.7	0.9
Q	0.7	0.9	1	1	1	1	0	0.1	0.3	0	0.1	0.3	0.5	0.7	0.9	0.1	0.3	0.5
D	0.5	0.7	0.9	0	0.1	0.3	1	1	1	0.5	0.7	0.9	0.3	0.5	0.7	0	0.1	0.3
F	0.3	0.5	0.7	0.1	0.3	0.5	0.7	0.9	1	1	1	1	0.5	0.7	0.9	0.3	0.5	0.7
P	0.5	0.7	0.9	0.5	0.7	0.9	0.3	0.5	0.7	0.1	0.3	0.5	1	1	1	0.3	0.5	0.7
I	0.5	0.7	0.9	0.3	0.5	0.7	0.3	0.5	0.7	0.5	0.7	0.9	0.7	0.9	1	1	1	1

Table 5. The total relation matrix.

	C	Q	D	F	P	I
C	2.029233	1.795513	1.617931	1.694632	1.764429	1.658888
Q	1.735788	1.678583	1.337094	1.455012	1.60132	1.387805
D	1.514706	1.263646	1.388454	1.371973	1.23373	1.150883
F	1.841684	1.665435	1.5855	1.779387	1.695742	1.576388
P	1.833782	1.703286	1.430495	1.598728	1.787755	1.531724
I	1.742721	1.549935	1.35726	1.600236	1.578245	1.612278

The threshold is 1.5.

Table 6. The impact relation among factors.

	C	Q	D	F	P	I
C	2.029233	1.795513	1.617931	1.694632	1.764429	1.658888
Q	1.735788	1.678583	0	0	1.60132	0
D	1.514706	0	0	0	0	0
F	1.841684	1.665435	1.5855	1.779387	1.695742	1.576388
P	1.833782	1.703286	0	1.598728	1.787755	1.531724
I	1.742721	1.549935	0	1.600236	1.578245	1.612278

Table 7. Final results of DEMATEL analysis.

	R	D	R+D	R−D	Dispatcher	Receiver	Weights	Rank
C	10.56	10.70	21.26	−0.14		R	0.18599	1
Q	9.20	9.66	18.85	−0.46		R	0.16493	4
D	7.92	8.72	16.64	−0.79		R	0.14558	6
F	10.14	9.50	19.64	0.64	D		0.17186	2
P	9.89	9.66	19.55	0.22	D		0.17101	3
I	9.44	8.92	18.36	0.52	D		0.16062	5

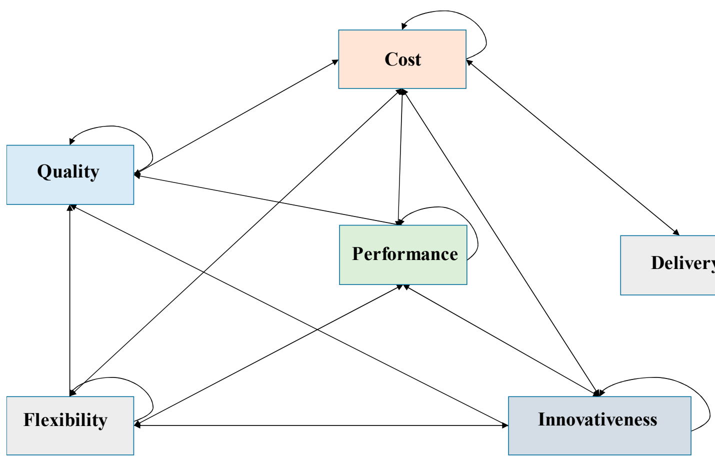

Figure 5. Interrelationships among MSOs.

4.2. Fuzzy TOPSIS Method

This part discusses how TOPSIS can be used to rank I4.0 technologies. Thus, the factors that most contribute to the overall differentiation of each technology can be identified, establishing a foundation for the development and implementation of effective improvement strategies. Due to space limitations in this study, Table 8 displays a sample of the collected data from one of the experts used to evaluate the alternatives in this study. Both positive and negative, fuzzy ideal solutions are illustrated in Tables 9 and 10. Consequently, the distances d_j^+ and d_j^- for each choice and the closeness coefficient CC_i for I4.0 technologies are displayed in Table 11. Figure 6 shows the closeness coefficients CC_i as well as the final ranking of I4.0 technologies.

Table 8. An example of collected data.

MSOs	IoT	CM	BD	AIR	AM	AR	MS	CPS	CS	BC
C	H	M	M	H	H	L	L	H	L	M
Q	M	L	H	VH	H	M	M	VH	L	M
D	VH	M	L	H	L	L	M	H	L	M
F	H	M	L	M	VH	H	H	H	L	M
P	H	M	H	H	M	L	H	VH	H	H
I	L	L	L	L	VH	M	M	H	VL	L

Table 9. Distance from fuzzy positive ideal solution (FPIS).

MSOs	IoT	CM	BD	AIR	AM	AR	MS	CPS	CS	BC
C	0.00804	0.00300	0.00067	0.00350	0.00712	0.00067	0.00000	0.10609	0.09819	0.09819
Q	0.04445	0.05290	0.04605	0.02138	0.02437	0.05382	0.05477	0.00000	0.06093	0.06659
D	0.03851	0.04670	0.05008	0.02032	0.04441	0.04834	0.05515	0.00000	0.05190	0.05283
F	0.03009	0.04241	0.03717	0.03349	0.02293	0.02710	0.02804	0.00000	0.04376	0.03232
P	0.04978	0.05780	0.05303	0.02453	0.02790	0.05303	0.04978	0.00000	0.05393	0.05393
I	0.05829	0.07187	0.06948	0.07361	0.00000	0.05934	0.06040	0.05152	0.08190	0.06948
d_j^+	0.22916	0.27467	0.25648	0.17683	0.12674	0.24230	0.24815	0.15761	0.39061	0.37334

Table 10. Distance from fuzzy negative ideal solution (FNIS).

MSOs	IoT	CM	BD	AIR	AM	AR	MS	CPS	CS	BC
C	0.1048	0.1055	0.1060	0.1054	0.1049	0.1060	0.1061	0.0000	0.0080	0.0080
Q	0.0394	0.0260	0.0357	0.0531	0.0459	0.0252	0.0244	0.0666	0.0214	0.0000
D	0.0337	0.0209	0.0191	0.0395	0.0230	0.0198	0.0013	0.0560	0.0187	0.0187
F	0.0173	0.0016	0.0079	0.0126	0.0315	0.0221	0.0205	0.0438	0.0000	0.0142
P	0.0141	0.0000	0.0078	0.0345	0.0299	0.0078	0.0141	0.0578	0.0063	0.0063
I	0.0336	0.0224	0.0237	0.0103	0.0819	0.0324	0.0313	0.0422	0.0000	0.0237
d_j^-	0.24286	0.17642	0.20018	0.25543	0.31707	0.21325	0.19767	0.26636	0.05436	0.07085

Table 11. Fuzzy TOPSIS final result.

I4.0 T.	FPIS (d_i^+)	FNIS (d_i^-)	CC_i	Rank
IoT	0.229	0.243	0.5145	4
CM	0.275	0.176	0.3911	8
BD	0.256	0.200	0.4384	7
AIR	0.177	0.255	0.5909	3
AM	0.127	0.317	0.7144	1
AR	0.242	0.213	0.4681	5
MS	0.248	0.198	0.4434	6
CPS	0.158	0.266	0.6283	2
CS	0.391	0.054	0.1222	10
BC	0.373	0.071	0.1595	9

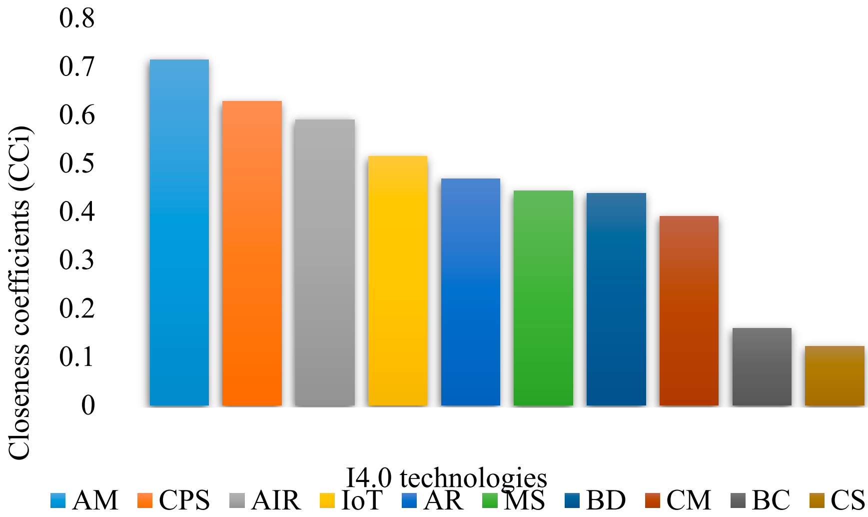

Figure 6. I4.0 technologies ranking.

Figure 6 depicts the ranking of I4.0 technologies and their respective closeness coefficients. Using Equation (34), these values were calculated. With a score of 0.714.4, AM outperformed all other Technologies in terms of market competitiveness. Frequently, additive manufacturing is seen as the most essential pillar of the I4.0 transition. This conclusion is supported by value and prior research. The capabilities of conventional production technology physically constrain intelligent factories. Since I4.0 requires mass customization, nontraditional production techniques must be developed [71].

Consequently, studies have shown that additive manufacturing is an essential component of I4.0 [71,72]. AM has become an important technology for making customized items due to its capacity to construct complicated objects with enhanced features (new materials, shapes). Due to its superior product quality, AM is applied in various areas, including aerospace and manufacturing [72]. The second technology is cyber-physical systems with 0.6283. Other technologies' rankings are shown in Figure 6.

The ranking of I4.0 technologies according to each MSOs

To evaluate the I4.0 technologies by each MSO, a weighted normalized average fuzzy decision matrix is used. The results of this ranking are displayed in Figure 7. It shows the relative relationships and the differentiation indices for each MSO's consolidated findings. The ranking of other I4.0 technologies according to each MSOs is shown in Figure 7. Table 12 demonstrates that the MS technology has the highest total score of 0.10874 out of all the I4.0 technologies concerning cost. This is followed by BD, CM, and AIR, each with scores of 0.10823, 0.10645, and 0.10606, respectively. Consequently, Table 12 reveals that various I4.0 technologies appear moderately or less critical in reducing costs.

Table 12. The weighted normalized average fuzzy decision matrix.

MSOs	IoT	CM	BD	AIR	AM	AR	MS	CPS	CS	BC
Cost	0.10259	0.10645	0.10823	0.10606	0.10329	0.10823	0.10874	0.00524	0.01192	0.01192
Quality	0.11935	0.10690	0.11624	0.14115	0.13492	0.10586	0.10482	0.15776	0.09860	0.08199
Delivery	0.06685	0.05885	0.05656	0.07542	0.06056	0.05770	0.04742	0.08684	0.05542	0.05485
Flexibility	0.09242	0.08378	0.08724	0.08983	0.10019	0.09501	0.09414	0.11574	0.08292	0.09069
Performance	0.08098	0.07441	0.07806	0.09703	0.09411	0.07806	0.08098	0.11235	0.07733	0.07733
Innovativeness	0.08155	0.07214	0.07371	0.06195	0.12546	0.08077	0.07998	0.08704	0.05646	0.07371

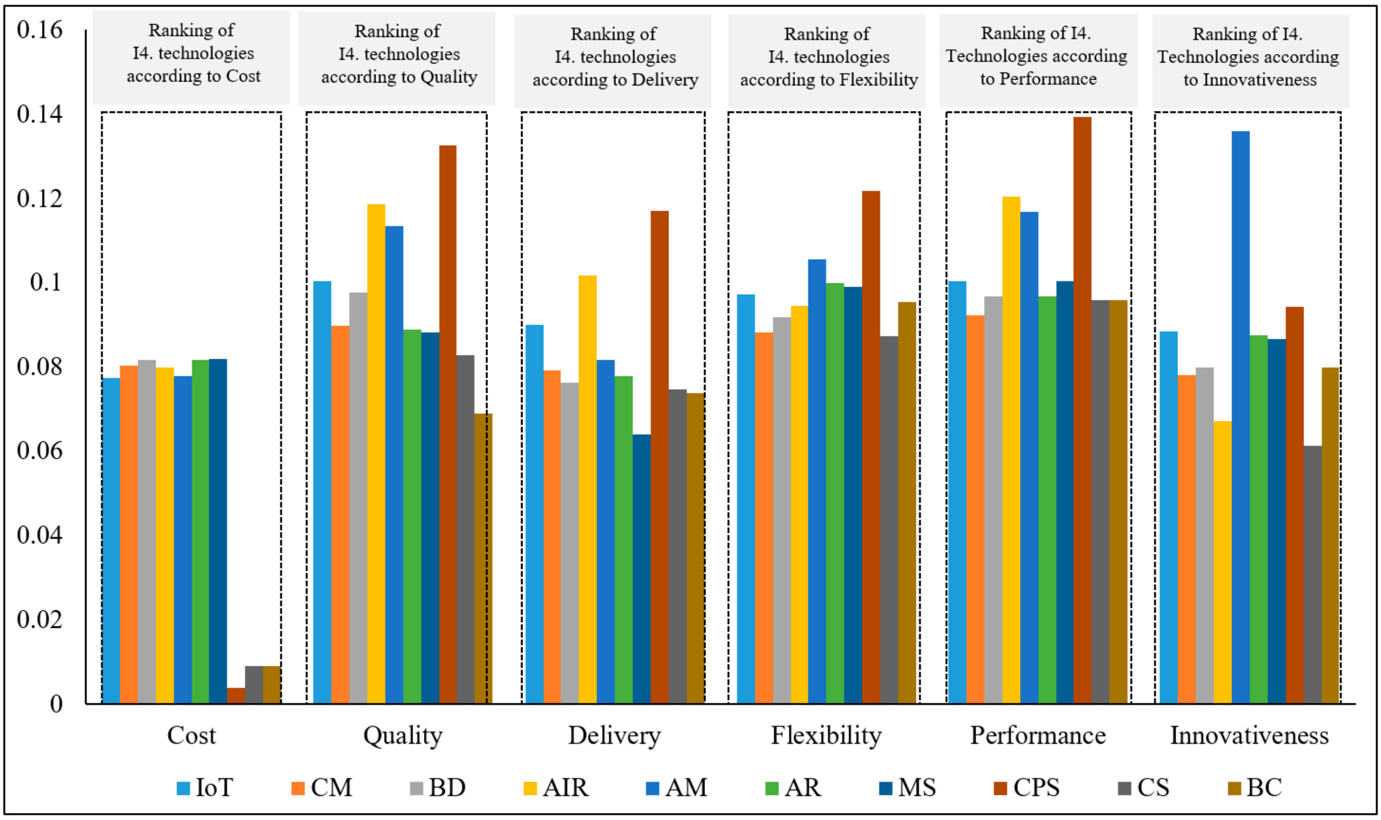

Figure 7. The ranking of I4.0 technologies according to MSOs.

The comparison of prior research on the ranking and selection for I4.0 technologies is summarized in Table 13. It indicates that they utilize a different approach for evaluating the influence of I4.0 Technologies on MSOs. The rankings and selection of I4.0 technologies in order to decrease cost, improve flexibility, improve performance, and improve innovativeness are the same. Due to the uncertainty and vagueness of human judgment, there is a small difference in the ranking and selection of I4.0 technologies on quality and delivery, which was not considered in the previously reported study.

Table 13. Comparisons between previous results and current findings considering I4.0 technologies selections.

	Research Findings	**Previous Study [25]**	**Technology Guideline Selection**
Method Used	**A Hybrid MCDM**	**Z-Score**	
Data Collection	**Expert Opinions**	**Expert Opinions**	
Cost	MS	MS	First
	BD	BD	Second
Quality	CPS	AIR	First
	AIR	BD	Second
Delivery	CPS	BD	First
	AIR	IoT	Second
Flexibility	AM	AM	First
	CPS	CPS	Second
Performance	CPS	CPS	First
	AIR	AIR	Second
Innovativeness	AM	AM	First
	CPS	CPS	Second

5. Implications

Researchers have placed a substantial emphasis on MSO-related I4.0 technologies in recent years. Unfortunately, a well-structured approach is currently lacking to help businesses evaluate and choose the most suitable I4.0 technologies. The purpose of this study is to rank different I4.0 technologies using a hybrid fuzzy MCDM approach and assess their potential and influence on MSOs.

This model provides insightful information to decision makers, practitioners, cluster managers, and smart manufacturing researchers. An important contribution to this field is identifying how I4.0 technologies affect MSOs. As the adoption of smart manufacturing methods develops, firms focus on the manufacturing systems' characteristics influenced by technology improvements. I4.0 technologies are the essential enablers required to create smart manufacturing systems. However, the degree to which and the specific technologies chosen for this purpose depends on the organization's strategic decisions regarding the desired level of smartness. The level of smartness describes the organization's readiness to deploy smart manufacturing for a specific process, manufacturing asset, and facility [73]. In each category, I4.0 technologies must be aligned with long-term strategic objectives to improve manufacturing performance [74,75].

To gain a better understanding of factors affecting MSOs' adoption of I4.0 technologies, FDEMATEL was utilized to study root cause-and-effect relationships of factors affecting MSOs' I4.0 adoption [64]. By identifying MSO receivers and dispatchers, the FDEMATEL results support the efficient development and implementation of long-term plans. It has also been used to determine the relative importance of MSO factors. Fuzzy TOPSIS was also utilized to prioritize the alternatives. MSOs are ranked based on a system's structure and the significant factors that influence it, allowing researchers and manufacturers to understand how I4.0 technologies are ranked.

Based on practical management implications, this report provides managers with critical insights for improving MSOs' utilization of I4.0 technologies. In order to be competitive in the market and receive useful feedback, managers should prioritize the right I4.0 technologies in their production plans, as shown in this study. This ranking of Technology leads to enhance performance and competition. According to the ranking, organizations may benefit from integrating these technologies into their already-established, well-designed procedures [76]. This study also shows that industrial companies are increasingly recognizing the importance of implementing I4.0 technologies to remain competitive or perhaps boost their market share.

6. Conclusions

This research aims to determine the impact of I4.0 technologies on MSOs. Using a hybrid MCDM approach, the I4.0 technologies are ranked. The contribution of this research is tremendous from both a practical and theoretical perspective. Identifying I4.0 technologies and MSOs contributes to a better understanding of the fourth industrial revolution. Quantitative research into the effects of I4.0 technologies on MSOs was conducted, strengthening the understanding of their interdependence. This research contributed theoretical considerations for future empirical studies of the connection between I4.0 and MSOs, specifically as it relates to MSOs' efforts to enhance their performance in order to increase their market competitiveness. According to the study's findings, manufacturers can improve their worldwide competitiveness by adopting I4.0 technologies. The article offers a unique perspective on how MSOs should prioritize I4.0 technologies. By providing a ranking, this article assists businesses to recognize the value in integrating these technologies into their existing, well-thought-out procedures. As a result of this competitiveness was increased and performance was enhanced. Moreover, this research enables firms to shift from conventional to smart manufacturing, demonstrating how these technologies can play a crucial part in gaining a competitive advantage for a business.

The results indicated that cost (C) was the most influential factor, followed by flexibility (F) and performance(P). Other criteria are often of moderate significance to MSOs when adopting I4.0 technologies. Additive manufacturing is the most effective I4.0 technology for competing in the global market, according to the research. Following that are AIR and CPS. Other I4.0 technologies are less important to MSOs for implementation.

In addition to these contributions and findings, this study has a few limitations that will be addressed in future research as follows:

- It is also possible to evaluate the impact of I4.0 technologies on MSOs using multi-criteria methods such as VIKOR, ELECTRE, GRA, SAW, etc.;
- So far, no significant case studies or empirical research have been conducted to determine how MSOs are affected by I4.0 technologies. So, an empirical study can be conducted in the future;
- As an extension of this research, several I4.0 technologies, such as digital twins and others, may be analyzed to enhance manufacturing;
- The initial criteria were established by identifying six MSOs and ten I4.0 technologies. Broader criteria set may have been applied by examining additional criteria and technologies.

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