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A Decision-Making Model for Predicting Technology Adoption Success

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Abstract: Advanced manufacturing technology (AMT) has the potential to significantly improve manufacturing performance and boost competitiveness in the global market. Investment in AMT remains a promising but potentially risky venture due to the numerous factors that must be considered before the full benefits of implementing a new technology can be realized. To respond to the reported risks and uncertainties, such as those revealed in the recent industrial revolution, it is very important to identify and classify the critical factors that can influence the success of AMT adoption early in the planning stage. Based on an extensive review of relevant literature, 32 critical factors are identified and classified into ten categories in this paper. A new multiple-input single-output (MISO) model is developed by combining the fuzzy Delphi method (FDM) and the fuzzy inference system (FIS) based on the objectives defined. The FDM is used to determine the critical factors, and the FIS addresses the general fuzzy multi-attribute decision-making (MADM) problem in order to evaluate and predict the percentage of AMT adoption success with an existing system. The model is validated using a numerical test bed, and the results show that the model is a proper tool for risk management in AMT implementation.

Keywords: advanced manufacturing technology (AMT); fuzzy Delphi method (FDM); fuzzy inference system (FIS); flexible manufacturing technology (FMT); multiple-attribute decision-making (MADM) model

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Citation: Tahriri, F.; Mousavi, M.; Galavi, H.; Sorooshian, S. A Decision-Making Model for Predicting Technology Adoption Success. *Processes* **2022**, *10*, 2261. https://doi.org/10.3390/pr10112261

Academic Editor: Andrzej Pawłowski

Received: 31 August 2022
Accepted: 24 October 2022
Published: 2 November 2022

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1. Introduction

Companies have introduced and implemented advanced manufacturing technology (AMT) since the 1980s in order to increase their potential for success in the local market and also expand their businesses' boundaries to the global market. One of the benefits of AMT is its ability to provide greater processing and product flexibility (amount of adaptability or responsiveness for any future modification in a product design, including new products and derivatives of current products) [1], improve product quality (reduction or elimination of waste, rework, and losses in the production process) [2,3], improve customer service (ensuring customer satisfaction with a product or service) [4,5], and enhance time efficiency (managing the time effectively to produce more results) [6,7]. According to [8], and [9], AMT also offers lower labor costs, reduced dependency on external suppliers, shortened lead time and time-to-market, increased market share, and better management control. Integration of AMTs with new-generation IT technologies such as blockchain and digital twins can produce even better outcomes [10,11]. Using blockchain may increase security and enhance the traceability and sustainability of the AMT systems, and digital twins is an important factor affecting the adoption of AMTs technology in firms. Past studies [12,13]

indicate that the fourth industrial revolution was ushered in by modernized technologies, which have resulted in many positive impacts for the manufacturing sector, since the revolution has accelerated the adoption of new technologies. The Industry 5.0, however, with its human focus, sustainability, and resilience is seen as assisting in delivering mass personalized products to customers with high speed and accuracy [14]. After all, investment in advanced technologies, arguably, remains a risky venture [13,15]. As a result, lately, AMT is requiring even more attention than before. To respond to the existing failure risks and uncertainty about success, the key aim of the present research is to submit a model to correctly predict the success of AMT applications prior to their implementation.

Advanced Manufacturing Technology (AMT)

In general, AMT can be classified as divided into hard and soft AMT segments. Soft AMTs consist of integrated systems and this segment is further sub-classified as logistic-related technology, flexible manufacturing technology (FMT), and computer-integrated manufacturing (CIM) [16]. Hard AMTs consist of intermediate and stand-alone AMTs. Intermediate AMTs consist of technologies pertaining to automated inspection and material handling. In contrast, stand-alone AMTs consist of technologies related to design and engineering, machining, fabrication, and assembly [17,18]. More details of AMTs' classification are shown in Figure 1, which provides an overall view of the technologies currently available in this context. AMTs involve three phases, namely, pre-implementation, implementation, and post-implementation [19–21]. Arrows in Figure 1 show the application area of the model developed in this paper.

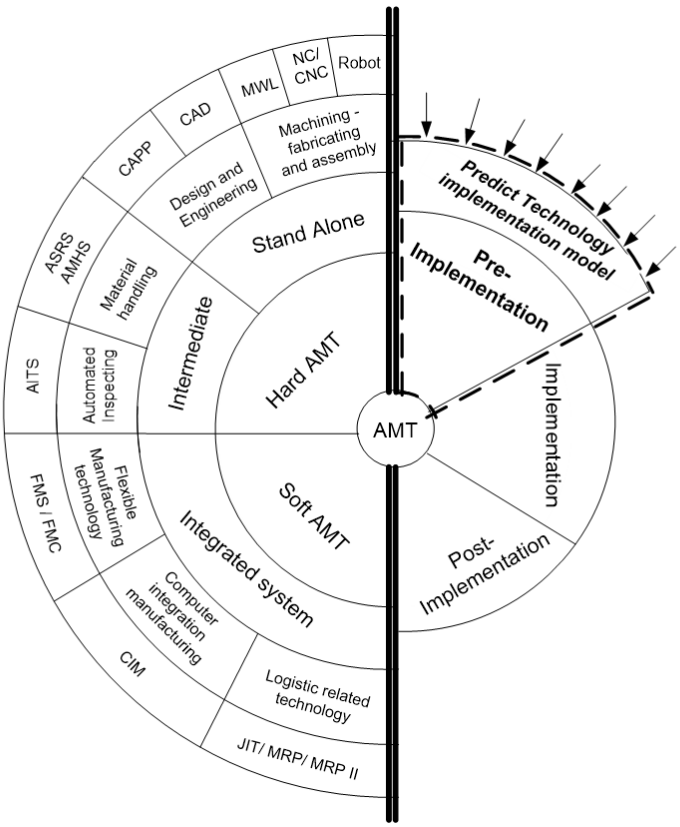


Figure 1. Classification of various advanced manufacturing technologies.

In general, the methods used to justify the implementation of AMTs can be classified as economic, strategic, and analytical methods. The primary difference between these methods lies in their treatment of non-monetary factors [22].

- Economic methods. Since financial matters are a crucial aspect in the manufacturing industry, it is vital for manufacturers to scrutinize the methods, which play a key role in achieving the desired target, such as payback methods, return on investment, and discounting cash flow methods. Even though these methods offer ease of data collection as well as intuitive appeal, they do not account for strategic and non-economic benefits, which managers need to address. In addition, these methods only consider a single objective for cash flow and neglect other benefits such as quality and flexibility [23].
- Strategic methods. Several manufacturers advocate the use of strategic methods in order to eradicate the drawbacks associated with conventional financial methods. These strategic methods cover technical importance, business objectives, competitive advantage, as well as research and development (R&D). Although these methods require fewer technical data and priority is given to the general objectives of the firm, there is one important factor which is typically overlooked by manufacturers since only long-term intangible benefits are considered, and it pertains to the use of strategic methods with either economic or analytical ones [24].
- Analytical methods. They can be used to evaluate and improve the promotion of manufactured products in order to gain business success. Analytical methods consist of scoring models (e.g., analytical hierarchy process (AHP)), mathematical programming, goal programming, integer programming, data envelopment analysis (DEA), stochastic methods, fuzzy set theories and multiple-attribute decision-making (MADM) [25].

There are two types of MADM methods; the first method involves selecting an alternative from a set of alternatives, which have been given scores, and the importance of the attributes for each alternative. In contrast, the second method involves ranking the alternatives using a role model or similar models [26], which will help manufacturers to account for future uncertainties associated with multiple objectives as well as incorporate subjective criteria during the modelling phase.

Figure 2 shows the conceptual framework of adopting new technology in supply chain management. This is classified into two main parts: independent and dependent variables. New technology helps factories to reduce cost, increase the firm's performance, intensify, build relationships with other parties, and increase response time. For adopting new technologies in the manufacturing system, three main stages are important; pre-implementation, implementation, and post-implementation. This adoptive technology can be used in SMEs, medium- and large-size factories.

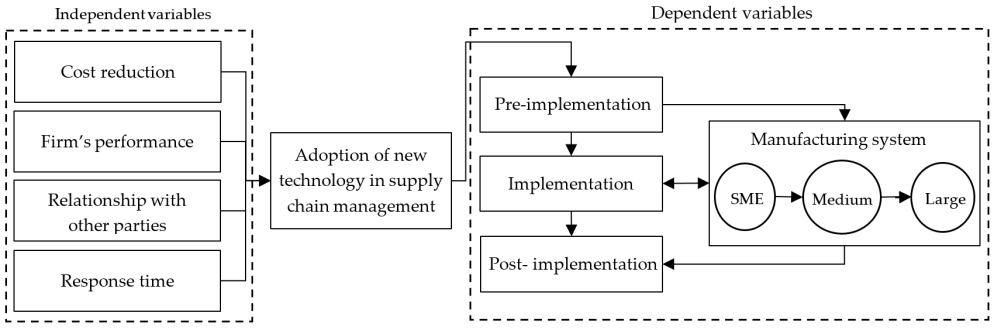


Figure 2. Adoption of new technology conceptual framework.

In this study, we first tried to identify the critical factors in AMT's successful adoption. Then, a fuzzy MADM approach was suggested, where the fuzzy Delphi method (FDM) and fuzzy inference system (FIS) are combined to develop a model to predict the percentage of successful adoption of AMTs. The model is a part of the pre-implementation phase.

2. Identification of Criteria for Advanced Manufacturing Technology

Implementing a new technology is a complicated process as there are numerous important factors which need to be considered to get the full benefits of AMT. This begs the question: 'what are the most influential factors affecting the successful adoption of AMT?' In order to address this, 67 articles related to AMT were reviewed and 32 factors were identified, as shown in Table 1. Most of the papers were published in peer-reviewed journals with high quality/h-index. It is therefore presumed that the information provided is reliable. Some of the keywords used to search for the papers were: advanced manufacturing technology, adoption, criteria, decision-making model. The most important factor for adopting AMT successfully is the 'strategy'. As adoption of AMT needs huge investment for the high cost of manufacturing, it needs special attention in the level of planning stage [27]. The accomplishment of business goals is supported by manufacturing strategy, by providing proper structural items (facilities, plant, equipment, etc.) and infrastructure items (control policies, human resources, economic, organizational structure, etc.) so that the operations can be ascertained as effective [28,29].

Efstathiades et al. divided the organizational structures into two strategic elements: knowledge and policies [30]. In order to implement AMT successfully, it is necessary to process changes in organizational infrastructure and practices, also obtain 'the worker's skills and knowledge'. The organization needs to adapt to new technology environments by focusing on the alignment of organizational and business factors [17]. A study on Spanish firms has shown that it is important to have 'top management support' for successful technology implementation [31]. In the same vein, [32] ranked 'top management support' as a first sub-objective for effective implementation of AMTs. Executives are committed sponsors who have a realistic understanding on the capabilities and limitations of technologies, and value these technologies to spend considerable time and energy in guiding their development. Operating sponsor is also another factor which affects the implementation of AMTs and refers to the case where the tasks are carried out frequently but are not always delegated to a trusted subordinate who becomes the operating sponsor or technology champion [33]. In addition, technology is innovative since it requires access to state-of-the-art knowledge and technology for successful implementation. Many organizations have successfully collaborated with academic institutions and/or used their research facilities to seek guidance and assistance in system development, as well as to seek technical knowledge to improve their technical skills and implementation. The present beliefs concerning the usefulness and integration of AMTs with the existing systems will either be dampened or heightened by personal beliefs on the effectiveness of AMTs [34].

Table 1. Identification of the critical factors which influence the successful implementation of AMTs.

	Strategy			**Financial**		**Organization and Business**			**Support**			**Technical**			**Management**			**Vendor/Supplier**		**Process/ Planning**		**Project Champion**			**Employee**		
	Operation Strategy	Strategic Management and Planning	Strategic Analysis and Motivation	Financial Evaluation	Economic Justification	Human Resource Management	Organizational Infrastructure and Culture	Alignment of AMT with Organization and Business	Top Management Support	Operating Sponsor	Support Systems before Equipment Installation	Governance and Commitment	Think-Tank Linkage	Knowledge and Perfecting Skills	Technical Infrastructure and its Influence on Successful Adoption	Technology Identification	Production Management and System	Managers experimenting with new Technologies	managers' Personal Beliefs and Understanding of AMT	Expectations of AMT	Commitment and Relationships with Vendors	Supplier-Related Factors	Selection of the Appropriate Technological Supplier(s)	Planning Process and Requirements	Product-Process Dependency	Integration of AMT with Existing Systems	Project Champions and Market Risk	Manufacturing Performance	Pilot Project	Training	Communication and Coordination	Lack of Knowledge and Skills
[35]	x					x						x									x										
[36]		x	x					x																							
[37]		x	x											x	x																
[19]		x						x							x		x		x												
[38]		x	x		x		x																								
[39]	x																	x	x								x				
[40]																								x							
[41]					x										x																
[33]																										x	x				
[42]								x			x				x																
[43]		x		x			x							x									x				x		x		
[31]									x														x						x		
[44]	x	x																													
[45]		x					x																						x		
[46]		x																											x		

Table 1. *Cont.*

	Strategy			Financial			Organization and Business			Support			Technical			Management			Vendor/Supplier			Process/ Planning		Project Champion			Employee		
[47]		x					x																				x		
[48]		x					x																				x		
[49]									x																				
[50]		x		x													x	x	x			x	x			x	x	x	
[51]		x			x		x			x					x														
[17]								x	x	x		x	x						x						x				
[30]																				x		x							x
[52]								x						x												x			
[32]									x													x					x		
[53]	x	x			x				x			x					x			x			x					x	
[54]	x						x	x									x												
[55]				x	x													x											x
[56]					x		x													x							x		x
[57]					x				x																				
[58]					x		x		x																		x		
[59]		x		x		x		x	x				x	x	x					x					x				
[60]	x						x						x				x									x			
[61]		x				x	x		x						x						x					x	x		
[21]		x				x			x	x			x		x							x		x			x		x
[62]	x			x													x				x			x				x	
[63]																								x					
[64]				x	x																			x					
[65]																x	x	x						x					
[66]				x	x							x				x	x							x					
[67]		x		x	x	x				x		x				x		x				x		x			x		
[68]	x							x		x			x	x										x					
[69]						x							x	x													x		x
[28]	x					x		x							x	x	x					x				x			
[70]	x			x					x					x						x									
[71]																		x						x					
[72]																								x					
[73]					x												x	x						x					
[74]				x	x							x				x	x												
[75]																								x					
[76]																	x								x				

Table 1. *Cont.*

	Strategy		Financial		Organization and Business			Support		Technical		Management			Vendor/Supplier	Process/ Planning		Project Champion				Employee		
[3]												x		x				x						
[77]			x	x					x			x	x	x				x						
[78]																		x						
[79]				x			x															x			
[80]				x			x							x	x							x			
[81]			x	x			x																		
[82]						x		x							x										
[83]	x																	x	x	x		x			
[84]									x		x						x	x							
[85]	x		x													x				x					
[86]			x																						x
[87]				x		x											x								
[88]	x						x														x	x			
[89]		x			x	x		x			x					x	x			x		x	x		
[90]						x		x									x					x	x		

3. Proposed Model to Predict the Success of AMT Adoption

The objective of this study is to develop a model, which predicts the percentage of success of AMT adoption. The methodology in this study consists of two main phases. The first phase involves applying the FDM to determine the critical factors which influence the successful implementation of AMTs. The second phase involves applying FIS to determine the percentage of success of AMT implementation. Figure 3 displays the structure of the fuzzy decision-making system (FDMS). This provides an example of all the qualitative and quantitative criteria used to test and validate the feasibility of the model.

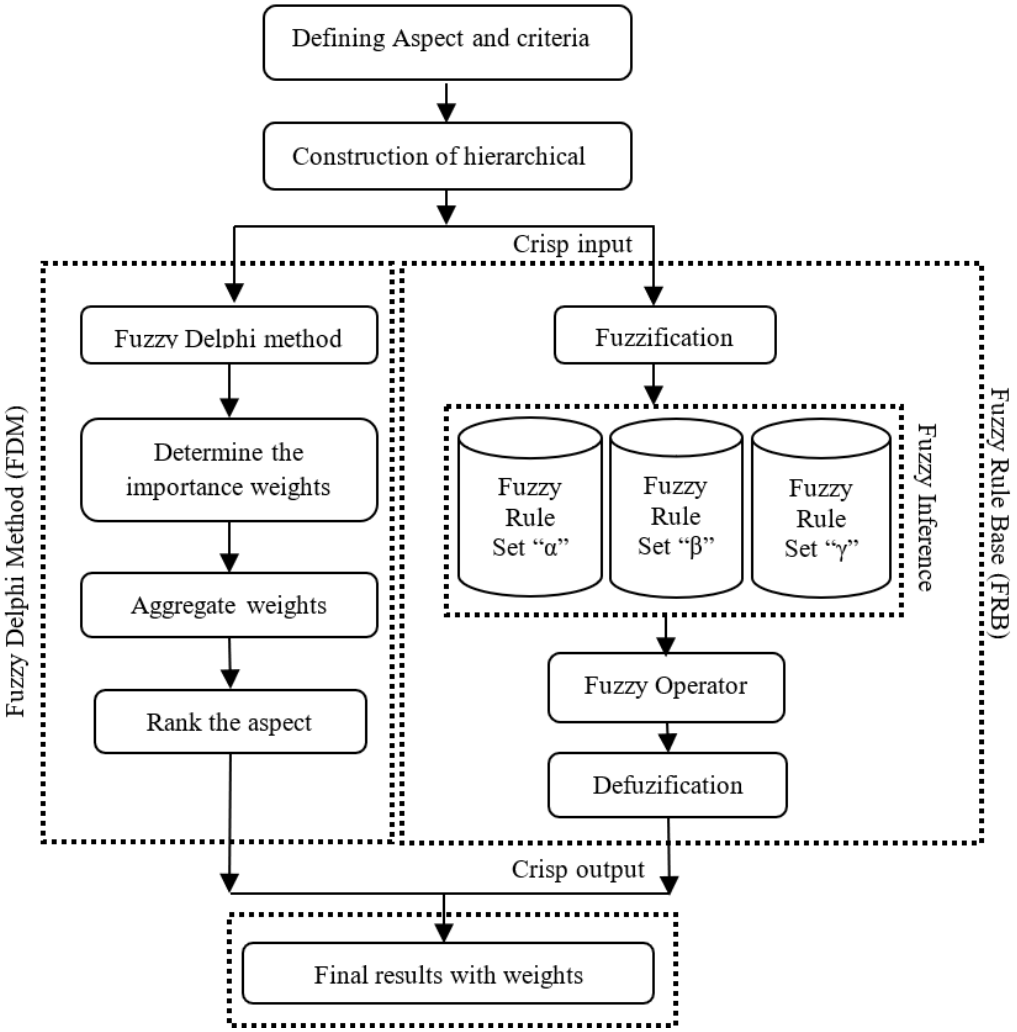


Figure 3. Process flow of fuzzy decision-making system (FDMS) structure.

The multi-criteria decision-making procedure is used to integrate both quality and quantity criteria in order to evaluate mutually exclusive prediction technologies for successful implementation of AMT [91].

Multi-criteria evaluation problem requires a number of criteria under every k criterion (C_1, C_2, . . . , Ck), taking into account the specific requirements of the problem. The criteria classified as (1) subjective criteria (C_1, C_2, . . . , Ch) which are defined in linguistic/qualitative terms and (2) objective criteria (C_{h+1}, C_{h+2}, . . . , Ck) which are defined in monetary/quantitative terms. These criteria construct the hierarchical structure of the primary model based on the aspects.

3.1. Fuzzy Delphi Method

Ref. [92] proposed FDM, which is based on the traditional Delphi method and fuzzy theory. Delphi is a method for gathering expert opinion that includes three components: anonymous response, iteration, and controlled feedback, as well as statistical group response. However, the Delphi method needs surveys in order to achieve a convergence of predicted values, making it time-consuming and costly [92,93].

The FDM is used to create a set of weight-pooled criteria. The triangular fuzzy numbers and linguistic variables are used to assess preference ratings in terms of the importance and appropriateness of linguistic variations.

The primary aim of the Delphi method is to achieve a common understanding of the group opinions using a questionnaire. However, this method is somewhat negated by the fact that it requires two-time provision of the questionnaire. Hence, the FDM was developed based on the fuzzy theory and offers the benefits of the Delphi method and eliminates the drawbacks associated with the conventional Delphi method [94,95].

In this study, FDM was used to screen the attribute factors in the first phase to solve the group decision [96] and fuzzy theory applied to solve and evaluate the fuzziness of common understanding among experts on a more flexible scale. The triangular membership function was also used to solve group decision-making. Accordingly, the efficiency and the quality of the questionnaires improved. It led to the increase in the number of objective evaluation factors that could be screened through the statistical results.

The steps of FDM are described briefly as follows:

1-Collect opinions of the decision-making group: a group of n decision-makers (D_1, D_2, . . . , D_n) choose to assess the importance weights of K quantitative and qualitative criteria (C_1, C_2, . . . ,C_k) [97] (Figure 4 and Table 2).

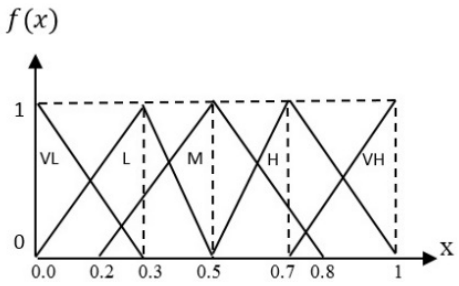


Figure 4. Membership functions for importance weights of criteria.

Table 2. List of linguistic variables and their corresponding fuzzy numbers for importance weights.

Linguistic Variables	Fuzzy Numbers
Very low (or VL)	(0.00, 0.00, 0.30)
Low (or L)	(0.00, 0.30, 0.50)
Medium (or M)	(0.20, 0.50, 0.80)
High (or H)	(0.50, 0.70, 1.00)
Very High (or VH)	(0.70, 1.00, 1.00)

2-Assigning triangular fuzzy numbers: for each factor given by the experts, the evaluation value and the significance of the triangular fuzzy number will be determined.

3-Aggregating expert opinions: mean of weight (W_t) obtained by the operation of fuzzy numbers and the linguistic terms transfer to positive trapezoidal fuzzy numbers. W_t represents the weight given to the subjective criteria C_1, C_2, . . . , C_{k-s} and objective criteria C_{k-s+1}, . . . , C_k by expert E_j.

$$W_t = (1/m) \otimes (E_j^1 \oplus E_j^2 \oplus \ldots \oplus E_j^m),\ t = 1, 2, \ldots,\ k \quad (1)$$

where $\otimes$ and $\oplus$ displays the multiplication and the summation of fuzzy numbers, respectively. E_j is a fuzzy number, which stands for the overall average weighting evaluation of alternative i under criterion j over m assessors. Equation (2) describes E_j by a triangular membership function:

$$W_t = \left(LE_j, ME_j, UE_j\right) \tag{2}$$

where the minimum of experts' common consensuses is shown as point LE_j, and the medium and maximum are shown as point ME_j and UE_j. The fuzzy weight $\widetilde{W}_t$ of element j is given by $\widetilde{W}_t = (a_t,\ b_t,\ c_t)$, where t = 1, 2,..., k. Note that:

$$LE_j = (\sum_{k=1}^{m} LE_j^k)/m,\ ME_j = (\sum_{k=1}^{m} ME_j^k)/m,\ UE_j = (\sum_{k=1}^{m} UE_j^k)/m \tag{3}$$

It should be noted that the fuzzy synthetic decision results, i.e., the weights of each criterion, are fuzzy numbers. As a result, the non-fuzzy ranking method must be used for all fuzzy numbers in each criterion. Non-fuzzy ranking, also known as defuzzification, is a method for converting fuzzy numbers into crisp real numbers. The primary goal of defuzzification is to find the best non-fuzzy performance (*BNP*) values. The centre-of-area defuzzification method was chosen due to its simplicity, as it does not require the personal judgement of the analyst [91]. The *BNP* value of a fuzzy number is given by:

$$BNP_j = \left[\left(UE_j - LE_j\right) + \left(ME_j - LE_j\right)\right]/3 + LE_j \ \ \forall\, j \tag{4}$$

3.2. Fuzzy Inference System

For the fuzzy inference system, four steps can be defined: 1. Fuzzifier, 2. Fuzzy rule set, 3. Fuzzy operator, and 4. Defuzzification. The steps are briefly presented here but they were described in detail previously in [91].

3.2.1. Fuzzifier

A fuzzy set $\widetilde{A}$ in the domain $\mathbb{R}$ is called a fuzzy trapezoidal number if its membership function has the shape represented by Equation (5) and has a core $[b, c]$, left width $\delta = b - a$, and right width $\beta = d - c$ [98]:

$$\mu_{\widetilde{A}}(x) = \begin{cases} 0 & x < a, \\ 1 - \frac{b-x}{b-a} & a < x \le b, \\ 1 & b < x \le c, \\ 1 - \dfrac{x-c}{d-c} & c < x \le d, \\ 0 & d < x \end{cases} \tag{5}$$

where $a, b, c, d \in \mathbb{R}$ and $\mu_{\widetilde{A}}(x)$ is between 0 and 1.

Fuzzy set is a class of objects with a continuum of grades of membership. Let X be a non-empty set and a domain of discourse where X= $\{x_1, x_2, \ldots, x_n\}$. A fuzzy (sub) set $\widetilde{A}$ of a domain of discourse X is a set of ordered pairs, which is given by:

$$\begin{gathered} \widetilde{A} = \left\{\left(x_1,\ \mu_{\widetilde{A}}\left(x_1\right)\right),\ \left(x_2,\ \mu_{\widetilde{A}}\left(x_2\right)\right), \ldots,\ \left(x_n,\ \mu_{\widetilde{A}}\left(x_n\right)\right) | x_1,\ x_2, \ldots,\ x_n \in \mathrm{X}\right\}, \\ \mu_{\widetilde{A}} : \mathrm{X} \to [0,\ 1], \end{gathered} \tag{6}$$

where $\mu_{\widetilde{A}}$ is a membership function or grade of a fuzzy set $\widetilde{A}$, whereby the accepted mathematical notation for $\mu_{\widetilde{A}}$ is $\mu_{\widetilde{A}}(x)$: X$\to$ [0, 1]. The membership function $\mu_{\widetilde{A}}\left(x_i\right)$ gives the membership degree of a generic element x_i to the fuzzy set $\widetilde{A}$.

This study uses multiple-input single-output (MISO) and trapezoidal fuzzy numbers. Three fuzzy sets ('Low', 'Average', and 'High') are shown in Figure 5. These linguistic

variables are used to evaluate the importance of the input and output variables and are equal to the range of 0–1.

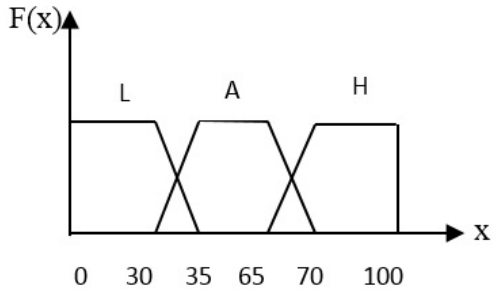


Figure 5. Three fuzzy sets in terms of 'Low', 'Average' and 'High' linguistic variables.

3.2.2. Fuzzy Rule Set

An essential element of fuzzy rule-based system is a set of IF-THEN linguistic rules, which have the following general form 'IF *A* THEN *B*'. Here, *A* and *B* are collections of propositions containing the linguistic variables. If there are *i* rules (R_i), each with *k* premises in the system, the *i*th rule has the following form:

$$R_i\text{: If } X_{i1} \text{ is } A_{i1} \text{ and } X_{i2} \text{ is } A_{i2} \ldots \text{ and } X_{ik} \text{ is } A_{ik}, \text{ then } Y \text{ is } B_i$$

In the above expression, *X* represents the crisp inputs to the rule and A_i and B_i are linguistic variables. X_{i1} to X_{ik} and *Y* represent the input variables and output variables for regression, respectively. The number of fuzzy rules used to control the system by means of fuzzy control is given by:

$$N = \sum_{j=1}^{m} \left(\prod_{i=1}^{n} Li \right) \tag{7}$$

where N is the total number of rules needed to control the system, *m* is the number of sets of rules that use the same set of variables, n is the number of input variables used in a set of rules, and L is the number of fuzzy sets (labels) in an input variable (i).

Based on the number of input variables for each aspect, related FIS engine rules are designed. Tables 3–5 show the MISO system rules with two, three, and four input variables, which are called α, β and γ rule respectively. The number of rules for each aspect is calculated independently based on the name of each rule.

3.2.3. Fuzzy Operator

The addition and multiplication of fuzzy operations are carried out for the proposed model. Let us suppose that Equations (8) and (9) are two trapezoidal fuzzy numbers, i.e.,

$$R = (r_1, r_2, r_3, r_4) \tag{8}$$

$$S = (s_1, s_2, s_3, s_4) \tag{9}$$

Hence, the addition of trapezoidal fuzzy numbers is given by:

$$R + S = (r_1 + s_1, r_2 + s_2, r_3 + s_3, r_4 + s_4) \tag{10}$$

and the multiplication of the trapezoidal fuzzy numbers is given by:

$$R \times S = (r_1 \times s_1, r_2 \times s_2, r_3 \times s_3, r_4 \times s_4) \tag{11}$$

Table 3. Fuzzy IF-THEN α rules.

Input 2	Input 1		
	L	**A**	**H**
L	L	L	A
A	L	A	A
H	A	A	H

Table 4. Fuzzy IF-THEN β rules.

Rule No.	Fuzzy Input Variables			Fuzzy Output Variables	Rule No.	Fuzzy Input Variables			Fuzzy Output Variables
	1	**2**	**3**	**Output**		**1**	**2**	**3**	**Output**
1	L	L	L	L	15	A	A	H	A
2	L	L	A	L	16	A	H	L	A
3	L	L	H	L	17	A	H	A	A
4	L	A	L	L	18	A	H	H	H
5	L	A	A	A	19	H	L	L	A
6	L	A	H	A	20	H	L	A	A
7	L	H	L	A	21	H	L	H	H
8	L	H	A	A	22	H	A	L	A
9	L	H	H	H	23	H	A	A	A
10	A	L	L	L	24	H	A	H	H
11	A	L	A	A	25	H	H	L	H
12	A	L	H	A	26	H	H	A	H
13	A	A	L	A	27	H	H	H	H
14	A	A	A	A					

Table 5. Fuzzy IF-THEN γ rules.

Rule No.	Fuzzy Input Variables				Fuzzy Output Variables	Rule No.	Fuzzy Input Variables				Fuzzy Output Variables	Rule No.	Fuzzy Input Variables				Fuzzy Output Variables
	1	**2**	**3**	**4**			**1**	**2**	**3**	**4**			**1**	**2**	**3**	**4**	
1	L	L	L	L	L	28	A	L	L	L	L	55	H	L	L	L	L
2	L	A	L	L	L	29	A	A	L	L	A	56	H	A	L	L	A
3	L	H	L	L	L	30	A	H	L	L	A	57	H	H	L	L	A
4	L	L	A	L	L	31	A	L	A	L	A	58	H	L	A	L	A
5	L	A	A	L	A	32	A	A	A	L	A	59	H	A	A	L	A
6	L	A	H	L	A	33	A	A	H	L	A	60	H	A	H	L	H
7	L	H	A	L	A	34	A	H	A	L	A	61	H	H	A	L	H
8	L	H	H	L	A	35	A	H	H	L	A	62	H	H	H	L	H
9	L	L	A	A	A	36	A	L	A	A	A	63	H	L	A	A	A
10	L	L	A	H	A	37	A	L	A	H	A	64	H	L	A	H	H
11	L	A	A	A	A	38	A	A	A	A	A	65	H	A	A	A	A
12	L	A	H	A	A	39	A	A	H	A	A	66	H	A	H	A	H
13	L	A	H	H	A	40	A	A	H	H	H	67	H	A	H	H	H
14	L	H	A	A	A	41	A	H	A	A	A	68	H	H	A	A	H
15	L	H	H	H	H	42	A	H	H	H	H	69	H	H	H	H	H
16	L	H	A	H	A	43	A	H	A	H	A	70	H	H	A	H	H
17	L	H	H	A	A	44	A	H	H	A	H	71	H	H	H	A	H
18	L	L	H	L	L	45	A	L	H	L	A	72	H	L	H	L	A
19	L	L	H	A	A	46	A	L	H	A	A	73	H	L	H	A	H
20	L	L	H	H	A	47	A	L	H	H	A	74	H	L	H	H	H
21	L	A	A	H	A	48	A	A	A	H	A	75	H	A	A	H	H
22	L	L	L	A	L	49	A	L	L	A	A	76	H	L	L	A	A
23	L	A	L	A	A	50	A	A	L	A	A	77	H	A	L	A	A
24	L	H	L	A	A	51	A	H	L	A	A	78	H	H	L	A	H
25	L	L	L	H	L	52	A	L	L	H	A	79	H	L	L	H	A
26	L	A	L	H	A	53	A	A	L	H	A	80	H	A	L	H	H
27	L	H	L	H	A	54	A	H	L	H	H	81	H	H	L	H	H

3.2.4. Defuzzification

The input for the defuzzification procedure is a fuzzy set, i.e., aggregate output fuzzy set, whereas the output is only a single number. The centroid defuzzification method is expressed as follows:

$$X* = \frac{\int \mu_i(x) x \mathrm{d}x}{\int \mu_i(x) dx} \quad (12)$$

where X* is the defuzzified output, μ_i (x) is the aggregated membership function and x is the output variable.

The final results are determined based on each weight assigned to each aspect and the values assigned to each fuzzy output criterion.

$$\text{Final result} = \frac{\sum_{i=0}^{n} \left(\frac{\int \mu_i(x) x \mathrm{d}x}{\int \mu_i(x) dx} \right) w_i}{\sum_{i=0}^{n} w_i} \quad (13)$$

where W_i represents aspect i, and $\mu_i(x)$ is the aggregated membership function and x is the output variable.

Based on the final result, the AMT implementation is successful if the score is 50% or above. Likewise, the AMT implementation is a failure if the value is less than 50%.

3.3. Description of the Proposed Model

Figure 6 presents the proposed model in hierarchical structure based on the properties of the aspects, as well as input variables in crisp non-fuzzy numbers and output variables. The model is used to forecast AMT implementation success. It should be noted that all the rules are evaluated concurrently using fuzzy reasoning. Based on the rules, the results of each non-fuzzy number aspect are combined and defuzzified. The results are then calculated by multiplying the non-fuzzy weight of each feature by the values assigned to each fuzzy output criterion. The AMT implementation prediction model is evaluated based on 10 aspects and 32 criteria, as shown in Table 6. An overall agreement among experts is needed to form a hierarchical structure based on the FDM model.

Table 6. List of aspects and corresponding criteria.

No.	Fuzzy Output Variable		Fuzzy Input Variable
1	Strategy (A_1)	1.1	Operation Strategy (C_{11})
		1.2	Strategic Management and Planning (C_{12})
		1.3	Strategic Analysis and Motivation (C_{13})
2	Financial (A_2)	2.1	Financial Evaluation (C_{21})
		2.2	Economic Justification (C_{22})
3	Organization/Business (A_3)	3.1	Human Resource Management (C_{31})
		3.2	Organizational Infrastructure and Culture (C_{32})
		3.3	Alignment of AMT with Organization and Business (C_{33})
4	Support (A_4)	4.1	Top Management Support (C_{41})
		4.2	Operating Sponsor (C_{42})
		4.3	Support Systems before Equipment Installation (C_{43})
		4.4	Governance and commitment (C_{44})
5	Technical (A_5)	5.1	Think-Tank Linkage (C_{51})
		5.2	Knowledge and Perfecting Skills (C_{52})
		5.3	Technical Infrastructure and its Influence on Successful Adoption (C_{53})
		5.4	Technology Identification (C_{54})
6	Management (A_6)	6.1	Production Management and System (C_{61})
		6.2	Managers Experimenting with New Technologies (C_{62})
		6.3	Managers' Personal Beliefs and Understanding of AMT (C_{63})
		6.4	Expectations of AMT (C_{64})
7	Vendor/Supplier (A_7)	7.1	Commitment and Relationships with Vendors (C_{71})
		7.2	Supplier-Related Factors (C_{72})
		7.3	Selection of the Appropriate Technological Supplier(s) (C_{73})

Table 6. *Cont.*

No.	Fuzzy Output Variable		Fuzzy Input Variable
8	Process/Planning (A_8)	8.1	Planning Process and Requirements (C_{81})
		8.2	Product-Process Dependency (C_{82})
9	Project Champion (A_9)	9.1	Integration of AMT with Existing Systems (C_{91})
		9.2	Project Champions and Market Risk (C_{92})
		9.3	Manufacturing Performance (C_{93})
		9.4	Pilot Project (C_{94})
10	Employee (A_{10})	10.1	Training (C_{101})
		10.2	Communication and Coordination (C_{102})
		10.3	Lack of Knowledge and Skills (C_{103})

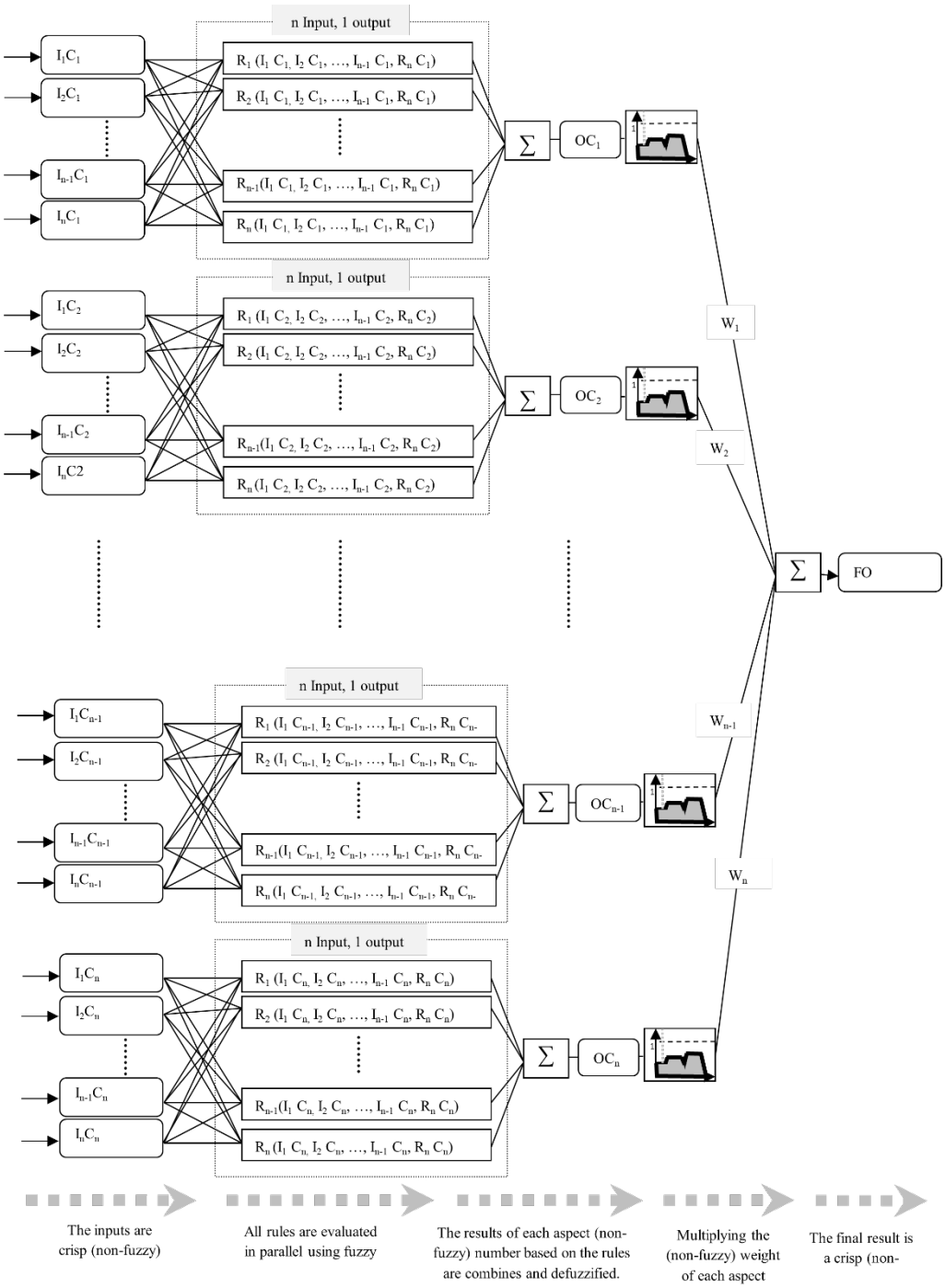


Figure 6. The hierarchical model of success for predicting implementation technology.

Three decision-makers called D_1, D_2, and D_3 use the weights to assess each aspect. A total of ten aspects are considered, namely, strategy (A_1), financial (A_2), organization/business (A_3), support (A_4), technical (A_5), management (A_6), vendor/supplier (A_7), process/planning (A_8), project champion (A_9), and employee (A_{10}). The membership functions and the linguistic variables for the importance weights of criteria are summarized in Figure 4 and Table 2, respectively. FDM is used to adjust the fuzzy weights of each expert in order to reach a consensus condition. The importance weights of all criteria for the three decision-makers are shown in Table 7.

Table 7. Importance weights for each aspect.

Aspect	D_1	D_2	D_3
A_1	VH	L	H
A_2	M	VL	H
A_3	VH	M	M
A_4	H	VL	L
A_5	H	H	VL
A_6	M	VH	VL
A_7	L	H	M
A_8	VL	H	VH
A_9	M	M	H
A_{10}	VL	L	VH

Table 8 shows the answers of experts to the FDM questionnaires which converted into positive triangular fuzzy numbers. The aggregate fuzzy weights for each criterion determined using Equations (1)–(4) and are shown in the fifth column of Table 8. The center-of-area defuzzification method is applied to convert the fuzzy numbers into crisp real numbers and the values are shown in the last column of Table 8.

Table 8. Average linguistic rating for each aspect in the AMT implementation prediction model.

Aspect	D_1	D_2	D_3	Fuzzy Mean = $\sum$ D	Value
A_1	(0.7, 1.0, 1.0)	(0.0, 0.3, 0.5)	(0.5, 0.7, 1.0)	W1 = (0.40, 0.66, 0.83)	0.630
A_2	(0.2, 0.5, 0.8)	(0.0, 0.0, 0.3)	(0.5, 0.7, 1.0)	W2 = (0.23, 0.40, 0.70)	0.443
A_3	(0.7, 1.0, 1.0)	(0.2, 0.5, 0.8)	(0.2, 0.5, 0.8)	W3 = (0.36, 0.66, 0.86)	0.626
A_4	(0.5, 0.7, 1.0)	(0.0, 0.0, 0.3)	(0.0, 0.3, 0.5)	W4 = (0.16, 0.33, 0.60)	0.363
A_5	(0.5, 0.7, 1.0)	(0.5, 0.7, 1.0)	(0.0, 0.0, 0.3)	W5 = (0.33, 0.46, 0.76)	0.516
A_6	(0.2, 0.5, 0.8)	(0.7, 1.0, 1.0)	(0.0, 0.0, 0.3)	W6 = (0.30, 0.50, 0.76)	0.500
A_7	(0.0, 0.3, 0.5)	(0.5, 0.7, 1.0)	(0.2, 0.5, 0.8)	W7 = (0.23, 0.50, 0.76)	0.496
A_8	(0.0, 0.0, 0.3)	(0.5, 0.7, 1.0)	(0.7, 1.0, 1.0)	W8 = (0.40, 0.56, 0.76)	0.573
A_9	(0.2, 0.5, 0.8)	(0.2, 0.5, 0.8)	(0.5, 0.7, 1.0)	W9 = (0.30, 0.56, 0.86)	0.573
A_{10}	(0.0, 0.0, 0.3)	(0.0, 0.3, 0.5)	(0.7, 1.0, 1.0)	W10 = (0.23, 0.43, 0.60)	0.420

Several scholars have studied the ranking of multi-aspect fuzzy numbers. In this study, the fuzzy numbers are ranked based on the ten aspects in the following order: $A_4 < A_{10} < A_2 < A_7 < A_6 < A_5 < A_9 = A_8 < A_3 < A_1$ and the results are tabulated in Table 9.

In this study, there are three different fuzzy rule sets for the ten aspects, which depend on the number of input criteria. The α rule is used when there are two input criteria (N2 $\alpha = 32$), whereas the β rule (N2 $\beta = 33$) and γ rule (N2 $\gamma = 34$) are used when there are three and four input criteria, respectively.

For example, the 'strategy (A_1)' aspect consists of three input variables, namely, 'operation strategy (C_{11})', 'strategy management and planning (C_{12})' and 'strategic analysis and motivation (C_{13})'. These input variables are used as the three trapezoidal membership functions, as shown in Figure 7. Following this, the fuzzy rules are formulated, whereby the collection of fuzzy rules approximately reflects the way humans think during the decision-making process. The fuzzy rules for MISO systems are based on the number of

input variables, as shown in Tables 3–5. For instance, the β rule set (Table 4) is used to generate 27 fuzzy rules for the 'strategy' aspect, given that there are three input variables.

Table 9. Ranking of fuzzy aspects based on the α-cut set.

Rank	Aspect	Value
1	A_1	$H(A_1) = 0.630$
2	A_3	$H(A_3) = 0.626$
3	A_8	$H(A_8) = 0.573$
4	A_9	$H(A_9) = 0.573$
5	A_5	$H(A_5) = 0.516$
6	A_6	$H(A_6) = 0.500$
7	A_7	$H(A_7) = 0.496$
8	A_2	$H(A_2) = 0.443$
9	A_{10}	$H(A_{10}) = 0.420$
10	A_4	$H(A_4) = 0.363$

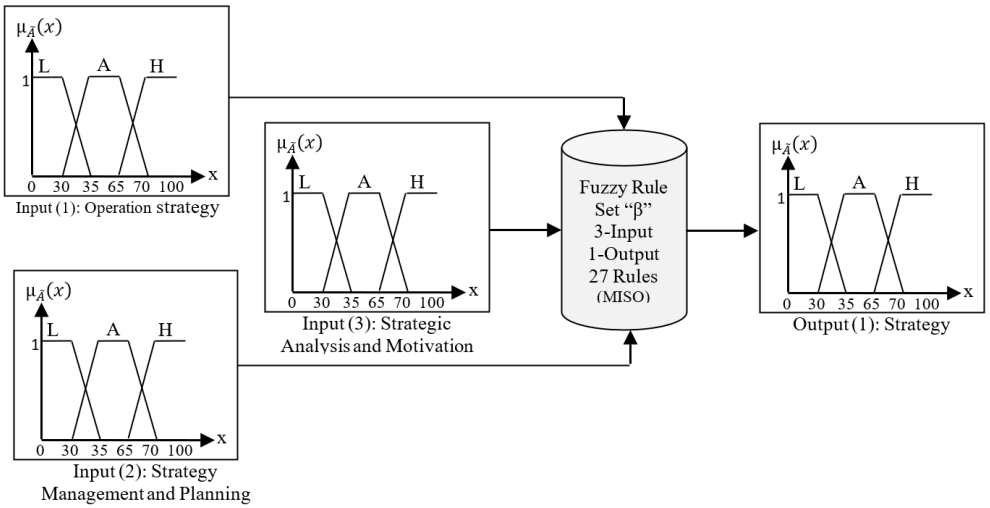


Figure 7. Multi-factor fuzzy inference system for strategy aspect (output 1).

One of the FIS is chosen as an example to demonstrate the structure of the rule viewer in the model. The rule viewer is indicative of the road network in FIS. Figure 8 shows the rule viewer of the FIS for the 'strategy' aspect. Each rule is represented by a row of plots whereas each column represents an input variable. In this example, the input variables painted yellow are 'operation strategy (C_{11})', 'strategic management and planning (C_{12})' and 'strategic analysis and motivation (C_{13})', whereas 'strategy (A_1)' represents the output variable or aspect painted blue. The input values can be varied by moving the red line and the FIS system correspondingly generates the output value. Since three membership functions are considered for the inputs, the number of rules is 27 in order to generate the output value (Table 10). Once the rules have been verified, it is clear that the output value (strategy) increases with an increase in the input values. The three rules are placed together in order to demonstrate how the output of each rule is combined or aggregated into a single fuzzy set value, which yields output (A_1) = 57.6 (Equation (12)).

The overall rate (Equation (13)) is calculated based on the fuzzy Delphi weight values of each aspect and the fuzzy rule-based values of each fuzzy output criterion (Table 11). The overall rate of the predicted AMT implementation (specifically robot technology) is 64.21%, which indicates the probability of successful AMT implementation. Since the overall rate exceeds 50%, the implementation of AMT falls within the successful range.

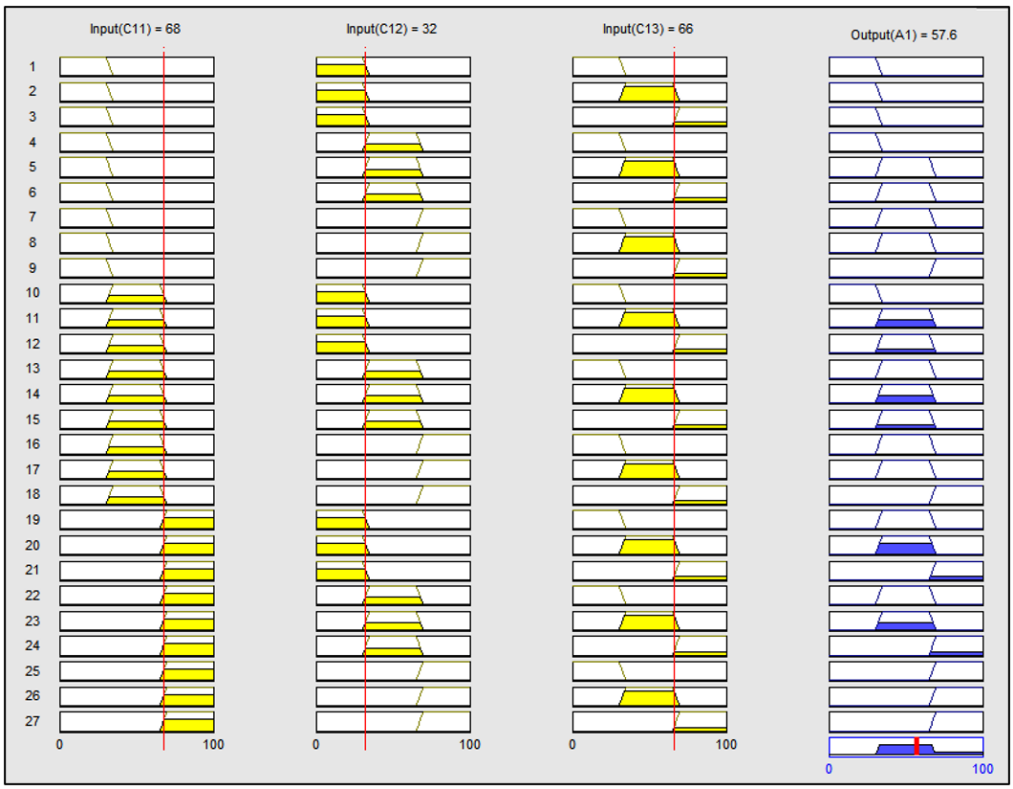


Figure 8. Rule viewer of the fuzzy inference system for strategy (A_1) aspect.

Table 10. Basic Fuzzy Rule-Based System, a summary.

Aspect	Aspect Name	No. of Inputs	Rule Name	No. of Rules	No. of Outputs	Conjunction Operator	Aggregation Operator	Inference Model
1	Strategy	3	β	27	1	Min	Max	Mamdani
2	Finance	2	α	9	1	Min	Max	Mamdani
3	Organization/Business	3	β	27	1	Min	Max	Mamdani
4	Support	4	γ	81	1	Min	Max	Mamdani
5	Technical	4	γ	81	1	Min	Max	Mamdani
6	Management	4	γ	81	1	Min	Max	Mamdani
7	Vendor/Supplier	3	β	27	1	Min	Max	Mamdani
8	Process/Planning	2	α	9	1	Min	Max	Mamdani
9	Project Champion	4	γ	81	1	Min	Max	Mamdani
10	Employee	3	β	27	1	Min	Max	Mamdani

Table 11. Final scores of the AMT implementation prediction model.

Fuzzy Input		Fuzzy Output		Weight of Aspect		Overall Value
Name	Value	Name	Value	Name	Value	
C_{11} C_{12} C_{13}	68 32 66	A_1	57.6	WA_1	0.630	36.28
C_{21} C_{22}	68 70	A_2	69.2	WA_2	0.443	30.65
C_{31} C_{32} C_{33}	82 98 12	A_3	35	WA_3	0.626	52.58

Table 11. *Cont.*

Fuzzy Input		Fuzzy Output		Weight of Aspect		Overall Value
Name	Value	Name	Value	Name	Value	
C_{41} C_{42} C_{43} C_{44}	23 36 45 78	A_4	65	WA_4	0.363	18.15
C_{51} C_{52} C_{53} C_{54}	45 62 67 68	A_5	24	WA_5	0.516	35.08
C_{61} C_{62} C_{63} C_{64}	46 52 69 78	A_6	16	WA_6	0.500	38.15
C_{71} C_{72} C_{73}	32 66 70	A_7	79	WA_7	0.496	28.56
C_{81} C_{82}	26 68	A_8	41	WA_8	0.573	21.43
C_{91} C_{92} C_{93} C_{94}	78 98 54 49	A_9	68	WA_9	0.573	48.13
C_{101} C_{102} C_{103}	68 45 20	A_{10}	93	WA_{10}	0.420	21
Final Prediction Result of Robot Technology Implementation = 64.21%						

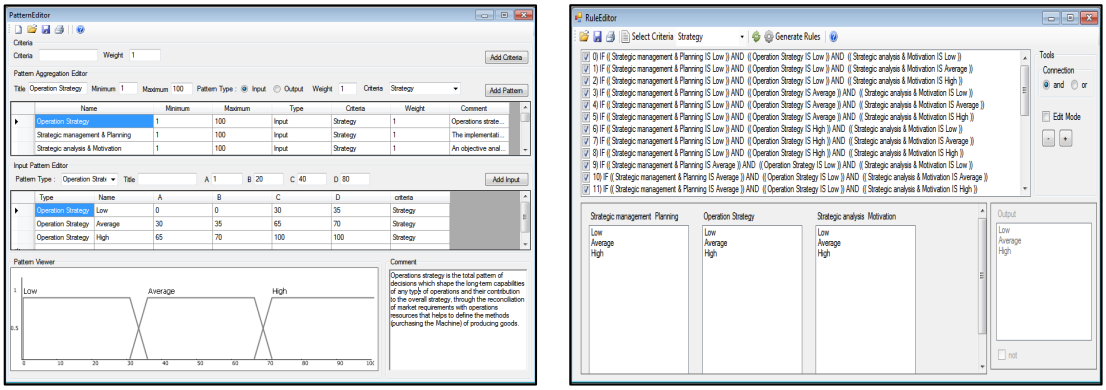
4. Supporting Tool

The model-supporting tool applied in this paper, is a C#-based implementation. This tool is developed to help managers in manufacturing firms to obtain results in a convenient manner. In fact, this tool offers the chance for decision makers to automate the specific steps of the decision-making procedure set out in Figure 3. The tool guides operators to express their judgments between all possible sets of functional and non-functional requirements in a similar way as the AMT decision-making approach does. Sample screenshots of the graphical user interface (GUI) of the software are shown in Figure 9a–d, which shows the 'rule editor', fuzzy Delphi, FIS, membership function editor, 'rule viewer', and 'final result viewer'. The GUIs provide users with tools to edit and observe fuzzy inference systems in the AMT prediction model. The 'rule editor' lets the user to read and modify the FIS data, whereas the fuzzy rules and final results of the FIS can be viewed in the 'rule viewer' and 'final result viewer', respectively.

The main user interface shows the membership and rule function menus. The 'pattern editor' is basically a FIS and membership function editor; it is used to define the input, output, and universal range for each variable. The 'pattern editor' enables the user to define and edit the FIS for all the membership functions associated with the input and output variables as shown in Figure 9a. The 'rule editor' is a feature provided in the tool, which enables the user to edit a list of rules, which are automatically created, based on description of the input and output variables (Figure 9b). The 'rule viewer' user interface displays the road network of the whole fuzzy inference process. The FIS is based on the fuzzy inference diagram described in the previous section. The criteria (aspect), sub-criteria (input variable), and its current value are displayed on the top pane of the user interface (Figure 9c). The 'final result viewer' user interface is presented in Figure 9d. The decision

maker can view the final results based on the input value of each criterion and will be able to make decisions.

(**a**) FIS, FD and membership Function Editor (**b**) Rule Editor



(**c**) Rule Viewer (**d**) Result Viewer

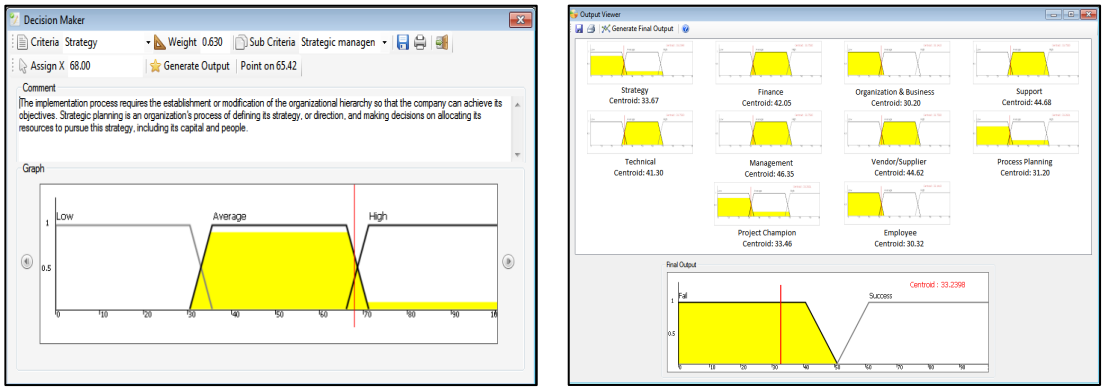


Figure 9. Screenshots of graphical user interfaces available in the AMT prediction tool.

5. Conclusions

The first outcome of this work is to identify the critical criteria that affect the successful implementation of AMTs in manufacturing firms. A total of 10 aspects including 32 criteria were identified. The aspects consisted of 'strategy', 'financial', 'organization/business', 'support', 'technical', 'management', 'vendor/supplier', 'process/planning', 'project champion', and 'employee'. 'Strategy', and 'organization/business' were ranked as the top two aspects. Another significant outcome of this article was to develop a multi-criteria decision-making model to assess and validate all criteria defined above in order to predict the percentage of AMT success. This prediction model for AMT was established by integrating FDM and FIS. The numbers of input variables for each aspect comprised the design of the rules for the FIS. Considering the name of each rule (α, β and γ), its number was separately calculated. The α fuzzy rule set consisted of 9 rules, whereas the β and γ fuzzy rule set consisted of 27 and 81 rules, respectively, which made a total of 117 rules. Whenever the overall rate of the model exceeded 50%, the implementation of AMT fell within the successful range. The model was tested using a numerical test bed and the result indicated that the AMT implementation with the rate of 64.21% was successful. By comparing various AMTs with the suitable criteria and aspects, the decision makers will be enabled to examine the strengths and weaknesses of technology implementations. The model is deemed beneficial, as it is applicable to various AMT implementation problems. A supporting tool was developed using C# programming software. It greatly facilitates the calculation of the percentage of success for the company, which intends to implement a particular AMT in order to reach consensus in the manufacturing firm, amongst decision-makers.

Author Contributions: Conceptualization, F.T., M.M. and H.G.; methodology, F.T.; validation, F.T. and M.M.; formal analysis, F.T.; data curation, F.T.; writing—original draft preparation, F.T.; writing—review and editing, M.M., H.G. and S.S.; supervision, F.T. and H.G.; project administration, F.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Full data is presented in the paper.

Conflicts of Interest: The authors declare no conflict of interest.

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