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Investigation and Classification of Failure Modes with Weighted Assessment using Various Fuzzy Logic Techniques

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Abstract: In the recent scenario, medium-scale automobile industries face daily challenges to maintain maximum quality and reliability amid multiple production procedures and limited available resources. This research presents a cohesive framework using various optimization techniques such as Fuzzy Failure Mode and Effects Analysis (FFMEA), Fuzzy Decision-Making Trial and Evaluation Laboratory (FDEMATEL), Fuzzy Analytic Hierarchy Process (FAHP), and Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS) to analyze failure mode rankings within production environments. In this case study, a medium–scale automobile industry is evaluated using a proposed model to identify failures, such as raw material delivery delays and limited supplier support. Results indicate that the cohesive fuzzy Multi-Criteria Decision-Making (MCDM) framework yields effective outcomes for reducing failures. Therefore, our proposed framework serves as a reliable tool for making informed decisions to optimize resource allocation in automobile manufacturing.

Keywords: Failure Modes, Automobile Industry, Manufacturing, FFMEA, FDEMATEL, FAHP, FTOPSIS

1. Introduction

The medium-scale automobile industry has become one of the most technologically advanced and competitive trades in the ecosphere. With an ever-increasing demand for better excellence, cost effectiveness, ecological approachability, and customer fulfilment automobile makers are continuously forced to optimize the manufacturing processes, minimize the wastage, and prevent failure losses [1-3]. In such an environment, any kind of slowdown in the production sectors due to machine and component failure, process incompetence, or quality issues can expressively impact production plans, customer associations, and overall productivity [4-6]. A wide range of sources, including design mistakes, human errors, equipment failures, and material shortages can lead to interruptions in today's complex manufacturing systems [7-8]. For affordability and operational superiority, it is vital to organize these failure modes initially and evaluate the effects on the production system. Judging and justifying these failure modes depresses the manufacturing process's overall susceptibility and weakness, in addition to the probability of production standstills and product recalls [9-10]. Old-style risk valuation approaches, such as Failure Mode and Effects Analysis (FMEA), have been used by the automobile manufacturing for years. FMEA thoroughly inspects possible failure modes, measures their causes and effects, and ranks them with a Risk Priority Number (RPN) calculated from Severity (S), Occurrence (O), and Detection (D) scores. FMEA offers a methodical way to study failures, but it has been criticized for being subjective, giving risk variables equal weight, and having trouble dealing the inaccuracy and ambiguity that come with expert opinion [11–12]. Due of this limitation, FFMEA was formed as a result of studies and applications that pursued to improve FMEA using fuzzy logic [13–15].

Fuzzy logic, derived from fuzzy set theory, offers a consistent approach to conduct the inaccuracy characteristic in language used in expert opinions. Experts can measure S, O, and D using fuzzy numbers like high, moderate, and low instead of working with precise values, appreciation to FFMEA. After that, a more complex and accurate risk ranking is calculated using these fuzzy values. Consequently, FFMEA offers a more accurate assessment of failure modes with uncertainty, especially in systems with a high level of complexity, such as automobile production [16-18]. Although FFMEA enhances individual failure modes evaluation, it does not take into consideration interdependencies and cause and effect relationships that exist between them. In an actual manufacturing environment, failure in one part may cause or affect others. Hence, it is important to know these cause and effect relationships to determine underlying causes and properly allocate resources to mitigate risks [19-20]. Fuzzy Decision-Making Trial and Evaluation Laboratory (FDEMATEL) has proven to be a powerful method for cause and effect mapping of these relationships. DEMATEL, particularly when coupled with fuzzy logic, facilitates visualizing and quantifying the level of influence between various failure factors, differentiating between cause and effect groups and facilitating improved strategic planning for avoiding failures [21-22].

Another critical aspect of failure mode evaluation is the relative importance or weight determination of each failure factor, particularly when there are several risk evaluation factors. This process is usually complicated, particularly in group decision-making situations with several experts having different opinions. The Fuzzy Analytic Hierarchy Process (FAHP) provides a systematic approach to managing such complexity. Through the implementation of fuzzy pairwise comparisons and hierarchical structuring, FAHP facilitates obtaining weights that express expert opinions optimally under conditions of vagueness and inconsistency, which prevail in environments of failure analysis [23-25]. Once the failure modes have been identified, their interdependences understood, and their respective weights determined, the last aspect of decision-making is to prioritize the failure modes. The Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS) is one of the most important Multi-Criteria Decision-Making (MCDM) methods applied for ranking alternatives according to their similarity to the ideal solution and difference from the worst situation [25-26]. FTOPSIS reflects fuzziness in decision-making and offers to rank failure modes [27-28].

This proposed framework begins with the identification of failure modes by FFMEA to address expert opinions. The relationships between failure modes are further investigated through FDEMATEL, indicating the cause and effect relations and assisting decision-makers in realizing the systemic behaviour of failures. Next, FAHP is utilized to determine the weightages. Finally, FTOPSIS ranks the failure modes based on the derived weightages, enabling clear and actionable prioritization. The arrangement of the article is as follows: Section 2 discusses key literature concerning the application of fuzzy-based MCDM tools. Section 3 describes the proposed approach comprehensively. Section 4 illustrates, through a case study, how the model has practical application. Section 5 explains the results and discussion, Section 6 concludes and Section 7 suggests for future work.

2. Literature Review

The manufacturing sector in the automobile industry operates in an extremely complex, dynamic, and competitive environment. To ensure productivity, quality, and cost, proactive identification, analysis, and remediation of prospective failure modes at different stages of manufacturing are highly important. It is therefore evident that there has been a widespread implementation of structured risk assessment techniques, in particular those which are guided by MCDM rules and fuzzy principles. This review of literature presents the evolution and application of four major fuzzy-based tools, such as FFMEA, FDEMATEL, FAHP, and FTOPSIS in the context of failure mode evaluation in manufacturing and vehicle systems.

One of the most common and oldest methods of failure determination is FMEA. FMEA identifies potential failure modes and classifies them into three determinants: S, O, and D and typically rates them into an RPN score (RPN = S × O × D). Conventional FMEA, however, is greatly criticized for subjective and biased rating, equating the risks, and no interdependencies among criteria [29]. To counter these limitations, FFMEA was created by combining fuzzy set theory with conventional FMEA. Fuzzy logic was created by Zadeh (1965) to deal with uncertainty and vagueness in human thought [30]. In FFMEA, expert linguistic ratings (i.e. high risk, low occurrence) are converted into fuzzy numbers, allowing for more realistic failure mode ranking. Liu *et al.* (2013) developed an integrated FFMEA model with triangular fuzzy numbers (TFN) to rank failures more accurately in industrial applications [31]. Whereas FMEA examines failure modes in isolation, actual systems tend to show interdependent and dropping failures. DEMATEL tries to compensate for this deficiency by simulating the causal interactions between system components [19-21]. Wu and Lee (2007) used fuzzy logic for DEMATEL to more accurately represent the uncertainty of expert judgment on influence levels [32]. AHP is a commonly used MCDM tool to obtain weights of criteria by pairwise comparisons. AHP, however, is based on exact numerical judgments, which do not reflect the linguistic nature of human judgment. For the sake of flexibility, FAHP was proposed by researchers, allowing fuzzy linguistic scales in comparisons [23-24]. FAHP has been extensively applied in the automobile sector. Cheng and Lin (2002) applied it to supplier selection to enable managers to evaluate factors such as cost, quality, and delivery using fuzzy logic [33]. Braglia *et al.* (2003) applied FAHP in balancing failure criteria in failure analysis in order to improve the prioritization process in maintenance planning [34]. FAHP's advantage is that it is able to manage multiple experts and give consistent weight distributions for complex hierarchical issues. The TOPSIS method, developed by Hwang and Yoon in 1981, is among the most well-known MCDM methods. The method allows for ranking alternatives based on their proximity to a best-case scenario ideal solution and a worst-case scenario negative ideal solution. FTOPSIS further develops the model to be used in uncertain environments by employing fuzzy numbers in the decision matrix [25-27]. FTOPSIS overcomes the rank reversal issue found in FAHP, resulting in more consistent and stable ranks [35]. FTOPSIS is particularly effective in failure mode ranking, where the criteria weights (from FAHP) and the ratings (from expert opinions) are imprecise. In the manufacturing sector, FTOPSIS was used for ranking the various machine failures [36], and to develop the engine project, it was also used to find out the risk ranking [37].

Fuzzy logic is used in automobile failure modes evaluation due to heavy reliance on linguistic descriptions and expert opinion rather than the frequent tests. Most important inputs on factory floors, such as S, O, and D are uncertain and nonlinear; this fuzzy set theory translates linguistic expert assertions, such as high, moderate, and low into mathematical functions and maintains uncertainty in ranking that captures ambiguity in human judgments [38-39]. This study suggests an integrated fuzzy model based on FFMEA, FDEMATEL, FAHP, and FTOPSIS for failure mode assessment in the automotive industry. This integrated process enhances the reliability of failure mode ranking and gives practical recommendations for process improvement and resource allocation.

3. Methodology

This research methodology proposes an integrated fuzzy MCDM model to assess failure modes in the manufacturing process of the automobile industry. The methodology used in this research has five prominent phases: (1) Failure mode identification via FFMEA, (2) Interrelationship identification via FDEMATEL, (3) Calculation of weight via FAHP, (4) Failure mode prioritisation via FTOPSIS, and (5) Ranking Comparison. The whole framework is illustrated in Figure 1.

The mathematical representation of the fuzzy process used in this study is discussed here. Firstly, nonnegative TFNs are written as, $\tilde{A} = (a_1, a_2, a_3)$. Then fuzzy addition, fuzzy multiplication and defuzzification were done by using, $\tilde{A} \oplus \tilde{B} = (a_1 + b_1, a_2 + b_2, a_3 + b_3)$, $\tilde{A} \otimes \tilde{B} = (a_1 b_1, a_2 b_2, a_3 b_3)$ and $Defuzz\,(\tilde{A}) = \frac{(a_1 + a_2 + a_3)}{3}$, respectively. After that, make a fuzzy decision matrix, $\tilde{X} = [\tilde{x}_{i,j}]$, $\tilde{x}_{i,j} = (x_{i,j}^1, x_{i,j}^2, x_{i,j}^3)$ along with m alternatives and n criteria.

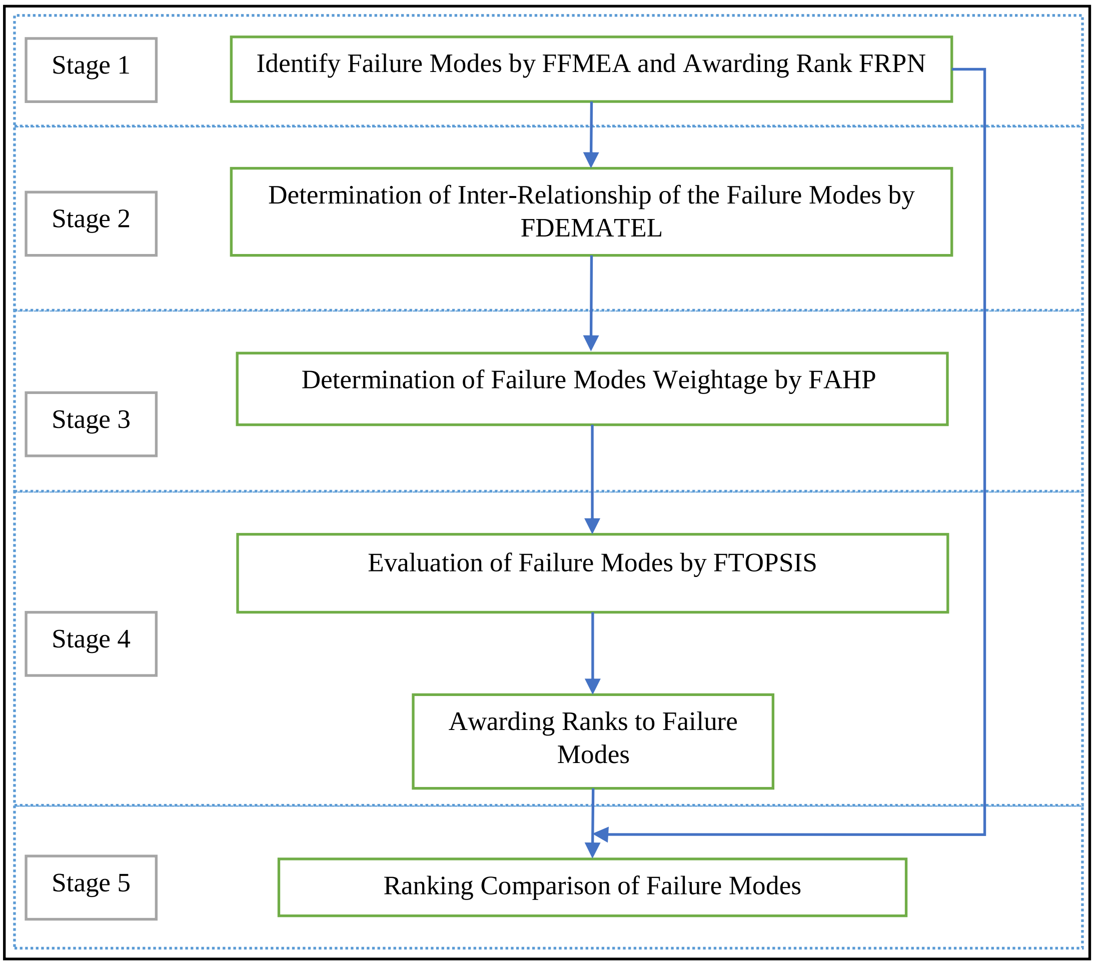

Figure 1. Proposed Methodology

Next fuzzy Positive Ideal Solution (FPIS) and fuzzy Negative Ideal Solution (FNIS) are calculated by using, $\tilde{v}_j^+ = (max_i\ v_{i,j}^1, max_i\ v_{i,j}^2, max_i\ v_{i,j}^3)$ and $\tilde{v}_j^- = (min_i\ v_{i,j}^1, min_i\ v_{i,j}^2, min_i\ v_{i,j}^3)$ respectively. After that, Euclidean-type distance was considered as S_i^+ means the distance of the ith alternative from the FPIS, $S_i^+ = \sum_{j=1}^n d(\tilde{v}_{i,j}, \tilde{v}_j^+)$ and S_i^- means the distance of the ith alternative from FNIS, $S_i^- = \sum_{j=1}^n d(\tilde{v}_{i,j}, \tilde{v}_j^-)$. And finally, calculate the closeness coefficient (CC_i)and ranking. To accomplish the process of ranking, the Microsoft Excel serves as the primary computational environment tools. Excel offers for conducting the all fuzzy-based computations, such as fuzzification, defuzzification, normalization, and ranking.

3.1. Failure Mode Identification through FFMEA

The procedure starts with the determination of possible failure modes from different operations of the automobile manufacturing system. Domain experts are consulted to determine the risk of each failure mode based on three important criteria, such as S (the impact of the failure on system performance or safety), O (the probability of the failure happening), and D (the probability of finding the failure before reaching the customer). In traditional FMEA, they are between 1 and 10. In this study, expert views are captured in linguistic terms (e.g., Low, Medium, High) and represented as TFNs, shown in Table 1 to reflect uncertainty and subjectivity. The Fuzzy Risk Priority Number (FRPN) for each failure mode is determined by applying fuzzy arithmetic on the S, O, and D values.

3.2 Developing Causal Relationships based on FDEMATEL

As failure modes are interact with each other, so cause and effect relationships are modelled using the FDEMATEL technique. The level of influence between pairs of failure modes is defined by experts in qualitative terms (e.g., No Influence, Low, Medium, High, Very High), which are then translated into TFNs, shown in Table 2. The fuzzy direct-influence matrix is normalized to obtain the total-relation matrix. The values for prominence (D'+R) and relation (D'−R) are determined for each failure mode, where D' is the total effect allocated to a specific failure mode, and R is the cumulative effects imposed on a specific failure mode. According to the value of relation, failure modes are categorized as, Cause group (net influencers of other failures) and Effect group (net recipients of influence).

3.3. Criteria weighting using FAHP

Once the failure mode inter-relationship is assessed, its relative importance is determined through the FFAHP. The experts perform pairwise comparisons of these failure modes based on fuzzy linguistic scales such as Equal, Moderate Strong, Very Strong and Extreme Importance, shown in Table 3.

Table. 1. Triangular Fuzzy Number for FFMEA

Linguistic Term	TFN (Triangular Fuzzy Number)			Remarks
	Low (L)	Medium (M)	High (H)	
Very Low	0	1	3	Reflects minimal severity or likelihood
Low	1	3	5	Low but not negligible failure influence
Medium	3	5	7	Represents an average or typical level
High	5	7	9	Represents strong severity or occurrence
Very High	7	9	10	Denotes the highest risk or impact

Table. 2. Triangular Fuzzy Number for FDEMATEL

Linguistic Term	TFN (Triangular Fuzzy Number)			Remarks
	Low (L)	Medium (M)	High (H)	
No Influence	0.00	0.00	0.25	Represents negligible relationship
Low	0.00	0.25	0.50	Small but measurable effect
Medium	0.25	0.50	0.75	Balanced influence strength
High	0.50	0.75	1.00	Clear cause-effect relationship
Very High	0.75	1.00	1.00	Reflects critical interdependence

Table. 3. Triangular Fuzzy Number for FAHP

Linguistic Term	TFN (Triangular Fuzzy Number)			Remarks
	Low (L)	Medium (M)	High (H)	
Equal	1	1	1	Baseline or neutral judgment
Moderate	2	3	4	Reflects mild preference
Strong	4	5	6	Represents definite dominance
Very Strong	6	7	8	Indicates very high preference
Extreme	9	9	9	Reflects the most decisive preference
Reciprocals	1/H	1/M	1/L	1/x

Table. 4. Triangular Fuzzy Number for FTOPSIS

Linguistic Term	TFN (Triangular Fuzzy Number)			Remarks
	Low (L)	Medium (M)	High (H)	
Very Low	0	1	3	Lowest possible rating
Low	1	3	5	Slightly better than minimal
Medium	3	5	7	Typical operational level
High	5	7	9	Consistently strong performance
Very High	7	9	10	Represents best-performing alternative

The fuzzy values from the comparisons are utilized to construct a consistent fuzzy pairwise matrix. The weights of the failure modes are then derived through the extent analysis method, and the results are defuzzified to get the correct weights.

3.4. Failure Mode Prioritisation using FTOPSIS

In the last phase, the failure modes are ranked against the weighted criteria based on FTOPSIS, a method that takes optimal as well as suboptimal scenarios into consideration. Failure modes are evaluated against all the criteria by using linguistic ratings that are converted into TFNs shown in Table 4. After that fuzzy decision matrix is weighted and multiplied by the weights obtained from FAHP. Then, the FPIS and FNIS are established. Fuzzy Euclidean distance is used to calculate the distance of each alternative (failure mode) from the FPIS and FNIS, and every failure mode's closeness to the optimum is gauged through the computation, $CC_i = \frac{S_i^-}{S_i^+ + S_i^-}$, where, S_i^+ means the distance of the ith alternative from the FPIS, and S_i^- means the distance of the ith alternative from FNIS. An overview of few important technical terms is given in Table 5.

4. Case Study: Application in a Medium-Scale Automotive Manufacturer

To support the effectiveness of the proposed model, a case study was performed in one of the medium-scale automobile component manufacturing factories. Table 6 provides the list of failure modes and the cause of their occurrence that summarized the key failure modes identified by the expert consultation and process observation. These failure modes cover human, machine, material and managerial aspects and hence represent the multidimensional nature of operational risk. The table provides a complete failure mode structure which can be used in analysis later, by taking all the internal shop floor problem, such as low-skilled workforce, machine failure, etc. and external supply based problem, such as delivery delay in raw materials supply etc. All the others tables record a unique output required to achieve the objectives, such as, identification of critical failure modes, interrelationships modelling, derivation of weights of criteria and prioritisation of risks in case of uncertainty. The following subsections elaborate on the relevancy and implication of the tabulated information.

Even though the company followed standard manufacturing practices, it still faced problems like parts not being the right size, jointing issues, paint shedding, and parts being rejected due to burrs or bending. These problems tended to cause more work, delays, and unhappy customers. The quality assurance team decided to use the suggested fuzzy-integrated system to deal with and reduce major failure problems. A team of five experts was formed with the quality manager, production supervisor, maintenance engineer, and two senior technicians. They brainstormed and reviewed previous quality history to identify 10 critical failure modes.

Table. 5. An Overview of Important Technical Terms

Term	Short Meaning
Fuzzified value	Fuzzy number from linguistic ratings.
Defuzzified value	Crisp value from fuzzy number using centroid method.
Defuzzified weight	Final crisp weight from FAHP fuzzy weights.
Closeness coefficient (CC_i)	used for FTOPSIS ranking.
FPIS / FNIS	Best and worst fuzzy reference points in FTOPSIS.
FRPN	Fuzzy risk score from $\tilde{S} \times \tilde{O} \times \tilde{D}$, then defuzzified.
Prominence (D’+R)	Total influence strength in FDEMATEL.
Relation (D’−R)	Indicates cause (+) or effect (−) in FDEMATEL.

Table. 6. List of the Failure Mode

Failure Mode	Reason
Delay in delivery of raw materials	Supplier inefficiencies, transportation issues, poor planning, or unforeseen external factors (e.g., strikes, weather)
Poor vendor quality	Lack of quality control by supplier, substandard raw materials, absence of certification or audits
Inadequate inspection process	Insufficient manpower, outdated inspection technology, lack of standardized procedures
Low-skilled workforce	Lack of proper recruitment, insufficient training, high turnover, no skill development programs
Outdated machinery	Budget constraints, lack of modernization strategy, reliance on old systems
Poor layout design	Inefficient space utilization, excessive movement of materials/workers, lack of ergonomic design
Lack of predictive maintenance	Reactive maintenance culture, budget issues, no IoT/sensor-based maintenance planning
Inefficient communication	Poor organizational structure, unclear reporting lines, lack of communication tools or training
Insufficient training	Budget cuts, time constraints, management undervaluing upskilling
In-process inventory control	Poor inventory tracking, lack of Kanban/lean systems, inaccurate forecasting

All failure modes were assessed on linguistic scales for S, O, and D. Furthermore, interdependencies between failure modes were examined using pairwise influence ratings for FDEMATEL.

4.1 FFMEA

Table 7 presents the fuzzy linguistic scales and corresponding TFNs used to evaluate S, O and D. The adoption of fuzzy representation addresses ambiguity and subjectivity inherent in expert judgment, which is a common limitation of conventional FMEA. This step fulfils the aims by enabling a more realistic risk assessment under uncertain industrial conditions. The FRPN values are also shown in Table 7, that indicate the relative criticality of each failure mode based on fuzzy S, O and D ratings. Higher FRPN values correspond to failure modes that position greater operational risk. Particularly, failure modes related to workforce competency and supplier reliability exhibit higher risk scores, highlighting areas requiring immediate managerial attention. This outcome establishes the baseline risk prioritisation necessary for causal analysis in the next stage.

4.2. FDEMATEL

Table 8 represents the fuzzy direct-relation matrix constructed using expert evaluations of interdependencies among failure modes. That values indicate the degree to which one failure mode influences another.

Table 7. Calculation of FRPN Value by FFMEA

Failure Mode	S			O			D			Defuzzified S	Defuzzified O	Defuzzified D	FRPN
	L	M	H	L	M	H	L	M	H				
Delay in delivery of raw materials	5	7	9	3	5	7	0	1	3	7.000	5.000	1.333	46.667
Poor vendor quality	3	5	7	1	3	5	0	1	3	5.000	3.000	1.333	20.000
Inadequate inspection process	3	5	7	1	3	5	3	5	7	5.000	3.000	5.000	75.000
Low-skilled workforce	7	9	10	3	5	7	0	1	3	8.667	5.000	1.333	57.778
Outdated machinery	5	7	9	1	3	5	3	5	7	7.000	3.000	5.000	105.000
Poor layout design	5	7	9	3	5	7	1	3	5	7.000	5.000	3.000	105.000
Lack of predictive maintenance	5	7	9	3	5	7	1	3	5	7.000	5.000	3.000	105.000
Inefficient communication	7	9	10	1	3	5	3	5	7	8.667	3.000	5.000	130.000
Insufficient training	7	9	10	3	5	7	1	3	5	8.667	5.000	3.000	130.000
Inprocess inventory control	3	5	7	1	3	5	3	5	7	5.000	3.000	5.000	75.000

Table. 8. Find the Cause and Effect Group by FDEMATEL

Factor	D' (Given)	R (Received)	Prominence (D'+R)	Relation (D'−R)	Group
Delay in delivery of raw materials	6.0	6.4	12.4	-0.5	Effect
Poor vendor quality	5.3	6.1	11.3	-0.8	Effect
Inadequate inspection process	6.6	7.6	14.2	-1.0	Effect
Low-skilled workforce	6.3	6.1	12.3	0.2	Cause
Outdated machinery	7.4	6.6	13.9	0.8	Cause
Poor layout design	5.7	6.2	11.9	-0.4	Effect
Lack of predictive maintenance	6.4	6.3	12.7	0.2	Cause
Inefficient communication	7.2	7.1	14.3	0.2	Cause
Insufficient training	6.6	5.6	12.2	0.9	Cause
Inprocess inventory control	7.2	6.7	13.9	0.4	Cause

This analysis addresses the aims by moving beyond isolated risk assessment and capturing the systemic interactions that exist in real manufacturing environments. The cause and effect grouping also presented in Table 8 classifies failure modes into cause (driving) and effect (dependent) categories. Failure modes in the cause group, such as insufficient training and outdated machinery, exert strong influence on other failures and therefore represent leverage points for improvement. This classification provides actionable insights for decision-makers and supports the aims by identifying root causes rather than symptoms.

4.3. FAHP

Table 9 represents the fuzzy weights derived using FAHP, reflecting the relative importance of each failure mode based on expert consent. Higher weights assigned to supply chain and inspection related failures indicate their strategic importance in maintaining production continuity. This step satisfies the aims by ensuring rational and consistent weighting prior to final ranking.

4.4. FTOPSIS

The final prioritisation results obtained through FTOPSIS are presented in Table 10. Failure modes with higher closeness coefficients (CC_i) are considered more critical due to their proximity to the ideal risk scenario. The ranking reveals that raw material delivery delays, poor vendor quality, and low-skilled workforce constitute the most critical risks, thereby fulfilling the aims of establishing a robust and decision-oriented prioritisation framework.

Table. 9. Calculated The Weightage by FAHP

Factors	Fuzzified			Weightage
	Low (L)	Medium (M)	High (H)	
Delay in delivery of raw materials	0.186	0.273	0.389	0.272
Poor vendor quality	0.127	0.185	0.264	0.184
Inadequate inspection process	0.109	0.158	0.230	0.159
Low-skilled workforce	0.108	0.143	0.197	0.144
Outdated machinery	0.070	0.095	0.134	0.096
Poor layout design	0.038	0.053	0.070	0.051
Lack of predictive maintenance	0.027	0.037	0.053	0.037
Inefficient communication	0.016	0.022	0.031	0.022
Insufficient training	0.014	0.018	0.025	0.018
Inprocess inventory control	0.011	0.016	0.024	0.016

Table. 10. Calculate Closeness Coefficient by FTOPSIS

Factors	Fuzzified			S_i^+	S_i^-	$S_i^+ + S_i^-$	CC_i
	S	O	D				
Delay in delivery of raw materials	0.120	0.098	0.066	0.062	0.150	0.212	0.707
Poor vendor quality	0.064	0.067	0.070	0.092	0.087	0.179	0.484
Inadequate inspection process	0.035	0.057	0.078	0.120	0.062	0.181	0.340
Low-skilled workforce	0.050	0.033	0.035	0.101	0.069	0.170	0.406
Outdated machinery	0.033	0.022	0.010	0.116	0.076	0.191	0.395
Poor layout design	0.011	0.012	0.012	0.139	0.066	0.205	0.322
Lack of predictive maintenance	0.013	0.013	0.014	0.137	0.065	0.202	0.321
Inefficient communication	0.005	0.008	0.005	0.146	0.072	0.218	0.331
Insufficient training	0.004	0.004	0.007	0.149	0.071	0.220	0.321
Inprocess inventory control	0.006	0.006	0.004	0.147	0.074	0.221	0.334

5. Results and Discussion

This section presents a comprehensive analysis of the results obtained from the application of the integrated fuzzy MCDM framework on the identified failure modes within a medium-scale automobile manufacturing unit. The findings highlight the performance of each method, such as FFMEA, FDEMATEL, FAHP, and FTOPSIS and they collectively contribute to more informed decision-making for failure mitigation in industrial settings.

5.1 FRPN value calculated using FFMEA

The first phase involved the application of FFMEA for initial risk evaluation. The TFNs representing the S, O, and D of each failure mode were aggregated using fuzzy arithmetic operations. The defuzzified FRPN provided a crisp risk ranking. Figure 2 presents the calculated FRPNs. Similar dominance of human-centric failure modes in FFMEA based assessments has been reported in recent studies, where training insufficiency and communication gaps were identified as primary contributors to operational risk in manufacturing systems [13, 16, 17]. The FFMEA results illustrate that each failure mode adds to effective concerns in a medium-scale automobile industry. The FRPN value disclose a dissimilar alteration in severity. Insufficient training and ineffective communication stand at the top with a FRPN of 130. These two criteria suggest restrictions in human resources and harmonization. When personnel lack proper training and communication lines are inadequate, mistakes grow, delays occur and inspection standards deteriorate. These human-centric challenges typically produce current effects over the full shop floor. FFMEA also found human-related factors such as communication gaps and training deficits to be the highest-impact risks in manufacturing systems, thus confirming the FRPN pattern from this study [13, 16, 31]. Both these works have also reported an improved differentiation of risks due to fuzzy scaling, especially for human-centric failure modes. A next group of dangers falls at the same intermediate level. Outdated machinery, poor layout design and lack of predictive maintenance each exhibit a FRPN of 105. These anxieties pertain to physical infrastructure. Poor layout and outdated machinery slow down motion, lower productivity, and increase the likelihood of failures. The absence of predictive maintenance means faults are not expected, which increases downtime and interrupts supply schedules. With scores of 75, inadequate inspection process and inprocess inventory control indicate a moderate level of risk. These shortcomings reflect inadequate quality assurance techniques and insufficient monitoring of materials inside the production process. Low-skilled workforce is slightly lower at 57.778, demonstrating that although skills gaps are existed, they are not as severe as training shortages or communication challenges. At the lower end of the list are delay in raw material delivery (46.667) and poor vendor quality (20). These figures show that while external supply-chain concerns do exist, they are not as serious as internal operational problems. The FFMEA reveals internal flaws are more disruptive than external reliance. Strengthening staff competencies, communication and machine upkeep should be the top concern.

5.2 Cause and effect analysis using FDEMATEL

FDEMATEL was implemented to identify the interrelationship between failure modes. Experts provided pairwise influence ratings, which were used to form the fuzzy direct-relation matrix. After defuzzification, prominence and relation values were computed to classify failure modes into cause-and-effect groups, as shown in Figure 3. This classification aligns with recent fuzzy DEMATEL applications, which consistently identify training, machine condition, and maintenance strategy as dominant causal factors influencing downstream quality and inspection-related failures in complex industrial systems [19, 21, 22]. According to the cause and effect diagram, the majority of internal elements are classified as cause, means they have an impact on other issues downstream. These include low-skilled workforce, outdated machinery, lack of predictive maintenance, inefficient communication, insufficient training and inprocess inventory control. This bunch demonstrates that poor internal systems and problems with human-machine interaction are the root causes of operational inefficiency. On the other hand, the effect category includes delay in raw material delivery, poor vendor quality, inadequate inspection process and poor layout design. The underlying reasons are what cause these factors. Inadequate training and inadequate communication frequently contribute to inspection mistakes. Material flow and layout use are impacted by outdated machinery. Past applications of FDEMATEL also identified that factors related to training, communication, and equipment condition tend to be in the core of the causal group that influences the downstream operational failures, consistent with the influence structure identified herein [20, 32]. Such studies reinforce the notion of automotive and industrial systems root causes that are more internal rather than supply-driven. The FDEMATEL results illustrated that addressing the inadequate inspection process and inefficient communication are the most interrelated failure modes with the others, as shown in Figure 4.

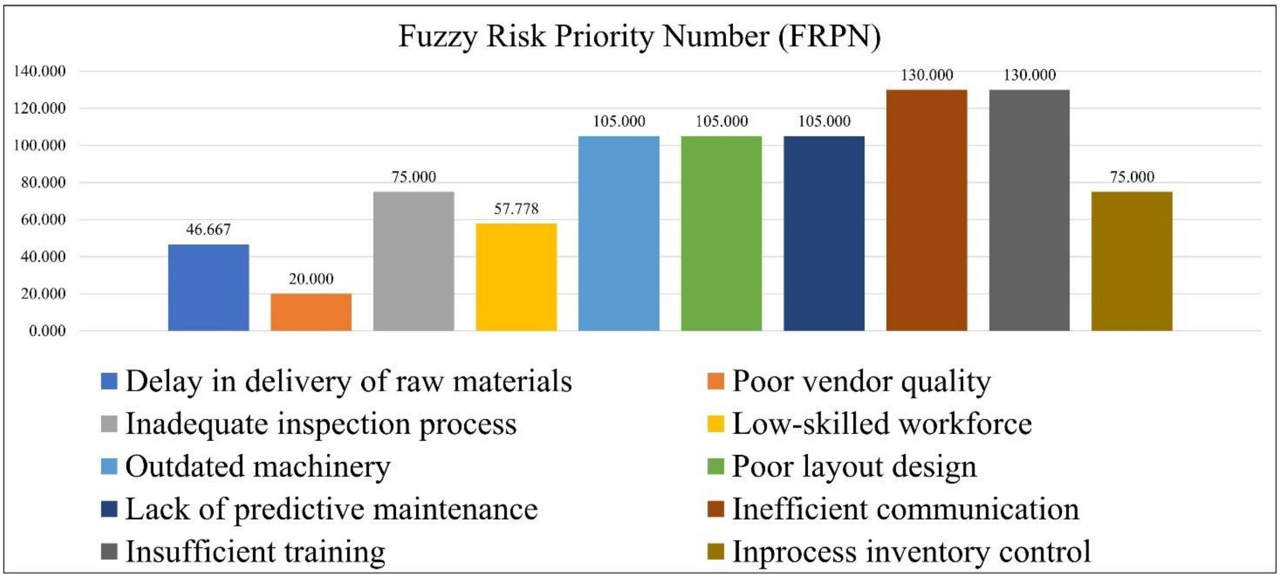

Figure 2. Calculated FRPN Value

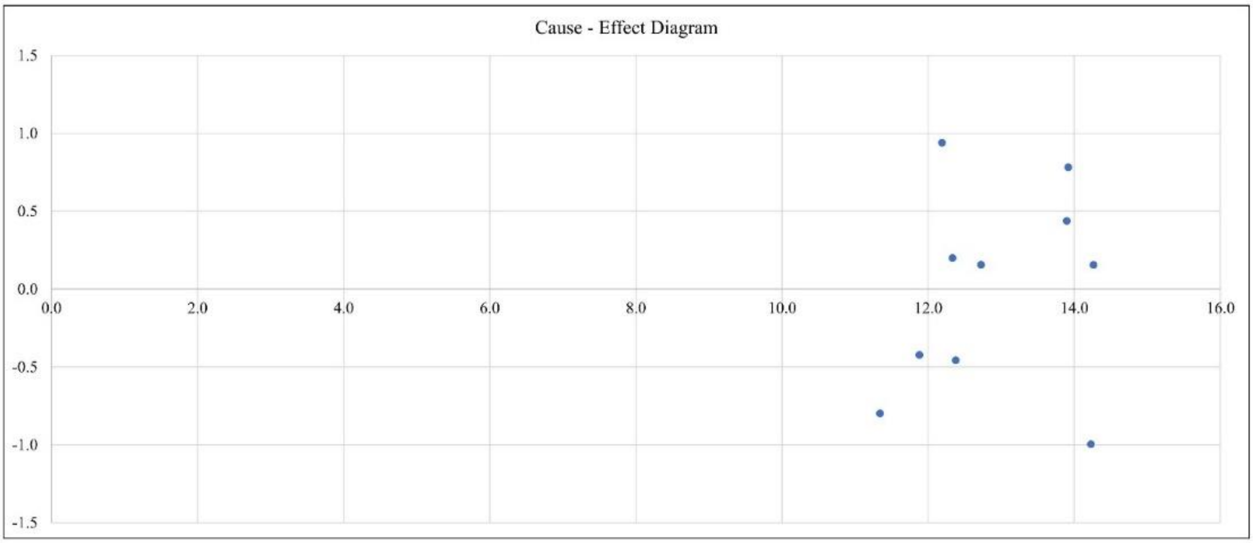

Figure 3. Cause and Effect Diagram

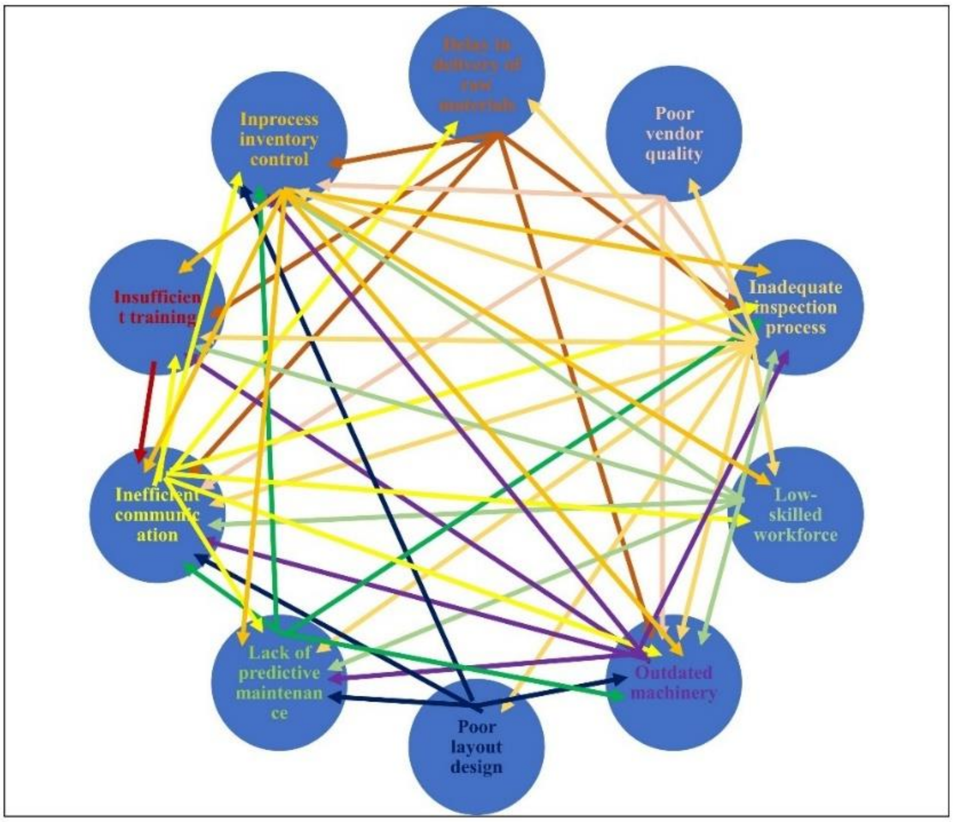

Figure 4. Inter-relationships between the Failure Modes

This diagram demonstrates substantial interdependencies across virtually all nodes. Strong impact channels are shown by thick directed arrows, particularly from outdated machinery, lack of predictive maintenance and insufficient training. A fundamental discovery from FDEMATEL is that enhancing training, communication and machine management can minimize numerous additional failure types concurrently. This strategy promotes the assumption that fundamental causes are mostly internal, whereas supply-chain-related concerns are secondary consequences.

5.3. Computation of weight using FAHP

FAHP was used to determine the relative importance of the evaluation criteria used in the final ranking of failure modes. Based on expert judgments and fuzzy pairwise comparisons, the weightage values were obtained as shown in Figure 5. Delay in delivery of raw materials rank highest in the findings, with a weight of 0.272. Even if its immediate operational risk is lower, experts view supply reliability as a crucial strategic concern, as evidenced by the fact that this looks greater than its FRPN score. Poor vendor quality (0.184) and poor inspection process (0.159) follow next.

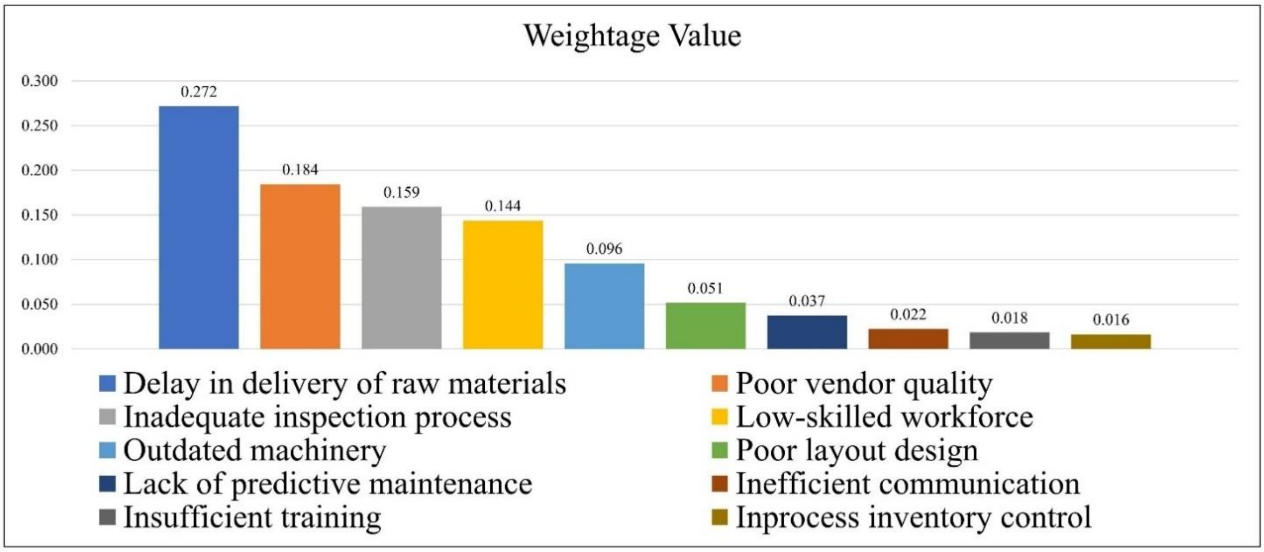

Figure 5. Weightage Value of Failure Modes

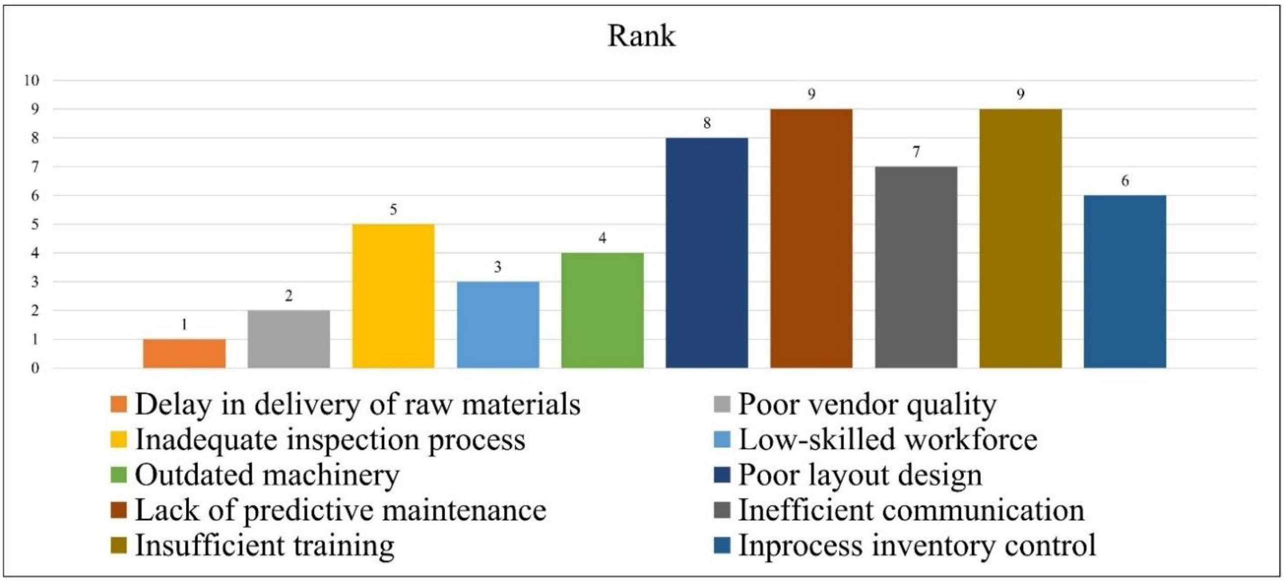

Figure 6. Ranking distribution for failure modes

These results demonstrate that sustaining consistent production depends on quality at both the supplier and inspection levels. Low-skilled workforce (0.144) and outdated machinery (0.096) fall in the mid-range. These are in line with FDEMATEL's assessment of machine and labor-related problems as contributing factors. Less important issues include inadequate layout design, ineffective communication, insufficient training and in-process inventory control.

Their low weights indicate that experts place a higher priority on supply reliability and quality systems rather than diminishing their significance. Comparable studies using FAHP have demonstrated that, despite seemingly moderate immediate operational risks, supply reliability and inspection quality tend to receive the highest expert weights in complex manufacturing settings [23, 33]. This agreement strengthens the weight distribution obtained in the current assessment.

5.4 Ranking using FTOPSIS

The final step involved prioritizing failure modes using FTOPSIS, which incorporates the previously calculated criteria weights and distances from the ideal and anti-ideal solutions. Closeness coefficients (CC_i) were calculated for each failure mode, as shown in Figure 6. The delay in delivery of raw materials (CC_i = 0.707), poor vendor quality (CC_i = 0.484) and low-skilled workforce (CC_i = 0.406) were the three biggest problems that needed to be addressed first. Ranking patterns from prior FTOPSIS studies also position supplier performance and material availability at the top of priority lists due to their systemwide influence on productivity and throughput. This further validates the prominence of supply chain related issues in our final closeness coefficient ranking. The highest-ranked concern is the delay in delivery of raw materials, which suggests that supply chain irregularity has the largest undesirable effect on productivity. When raw supplies do not arrive on time, manufacturing plans are disturbed, idle time increases and total throughput lowers. Poor vendor quality shows following, illustrating that external quality flaws generate rework, extra inspections and reduced dependability in final product. Low-skilled workforce and outdated machinery hold the third and fourth spots. These illustrate internal capability restraints where human and machine limits together decrease operational efficiency. Inadequate inspection methods rank fifth, demonstrating that gaps in quality assurance endure to allow faults to propagate downstream. In-process inventory control is positioned mid-range, suggesting modest effect on performance. Poor layout design and ineffective communication are the lowest levels. Although they impair workflow, their effect is significantly less severe than supply or quality-related issues. Lack of predictive maintenance and insufficient training share the ninth rank, signifying long-term concerns rather than immediate disruptions. The FTOPSIS results show that the three most important strategic areas that need immediate improvement are supply chain reliability, vendor quality and workforce capability. Recent fuzzy TOPSIS-based prioritization studies similarly report that supply-chain disruptions and vendor-related risks dominate final rankings due to their system-wide influence on throughput and delivery performance [25, 26, 27].

5.5 Comparative Discussion

The gap between FFMEA and hybrid fuzzy rankings is in line with the results of other integrated fuzzy MCDM models, where FMEA tends to give high importance to internal operational failures while the integrated models emphasize strategic susceptibilities, such as reliability of suppliers and consistency of inspections [34, 35]. This justifies the complementary role of the applied hybrid approach. The FFMEA identifies inefficient communication, insufficient training, lack of predictive maintenance, poor layout design, and outdated machinery as the most serious problems. These findings show that internal operational flaws, which have a direct impact on productivity and cause cascade interruptions across the manufacturing process, are the main causes of failure. In FFMEA, supplier-related issues like delay in delivery of raw materials, poor vendor quality seem less important as their incidence and severity are evaluated using fuzzy risk criteria that highlight internal process interdependence. The hybrid fuzzy ranking places delay in raw material delivery, poor vendor quality, and low skilled workforce problems at the top priority. These findings show the combined influence of weighted criteria and closeness coefficients, which convey expert preference and system-wide impact more strongly than separate risk ratings. In this paradigm, external supply chain difficulties outdated machinery and poor layout design and lack of predictive maintenance considerations. Recent studies have extended traditional FMEA by incorporating fuzzy logic and MCDM techniques to better handle uncertainty and complex interdependencies among risk factors. By integrating FMEA with DEMATEL has been shown to reveal cause and effect relationships that standard FMEA cannot capture, improving reliability analysis in manufacturing systems [40, 41]. Hybrid models combining FFMEA with fuzzy MCDM techniques (such as AHP or TOPSIS) have also been proposed to assign weights more systematically and rank alternatives under uncertainty, particularly in supplier selection and risk prioritization tasks [42, 43].

Table. 11. Comparative Discussion

Methods Used	Interdependency Analysis	Weighted Criteria	Ranking Method	Key Limitation
Traditional FMEA only [29]	No	Equal or simple	RPN	No uncertainty handling
FFMEA, DEMATEL [40]	Yes (causal links)	Limited	FMEA-based ranking	No multi-criteria weighting
Fuzzy FMEA & Fuzzy DEMATEL for ship operations [41]	Yes	Yes (via fuzzy interpretation)	Fuzzy prioritization	Lacks advanced MCDM final ranking
A New Hybrid Model Proposal for FMEA (FFMEA + fuzzy MCDM) [42]	Partial	Yes (e.g., FAHP)	TOPSIS or other	No integrated causal network
Hybrid Fuzzy AHP-TOPSIS for Supplier Selection [43]	No or limited	Yes	TOPSIS	Doesn’t include failure-cause analysis
Proposed Integrated Framework (FFMEA + FDEMATEL + FAHP + FTOPSIS)	Yes (causal network)	Yes (structured)	FTOPSIS robust ranking	—

Furthermore, combining DEMATEL's causal mapping with FTOPSIS enhances prioritization in complex decision problems, suggesting that a fully integrated model encompassing FFMEA, FDEMATEL, FAHP, and FTOPSIS can deliver a more robust and nuanced decision support framework than existing individual or partial hybrids. Table 11 presents a details comparative discussion that highlights and difference between the proposed model and existing methods. The main difference is that the hybrid fuzzy approach emphasizes supplier and inspection-related failures as the primary risks, whereas FFMEA prioritizes internal inefficiencies. When combined, the two strategies offer complimentary insights, such as, long-term system dependability will be strengthened by resolving supplier and inspection issues, while internal changes will stabilize daily operations. When combined, the framework results in a more comprehensive and convincing evaluation of failure modes. FAHP formalizes expert judgment, FDEMATEL reveals underlying systemic triggers, and FTOPSIS provides an actionable prioritization that takes into consideration, where FFMEA identifies immediate operational susceptibilities only. This results in a strong decision-support system that can more accurately direct resource allocation, maintenance scheduling, and quality enhancement in medium-scale automobile industry than any individual method alone.

6. Conclusion

This study presents an integrated fuzzy MCDM framework for the evaluation and prioritisation of failure modes within the manufacturing sector of the medium-scale automobile industry. Key failure modes such as delays in the delivery of raw materials, poor vendor quality, and a low-skilled workforce were identified as top priorities for improvement. The FDEMATEL analysis reveals essential cause-effect relationships, allowing for root cause identification and systemic intervention. FAHP ensures the evaluation criteria align. FTOPSIS then provides a final, weighted ranking that helps management make well-informed decisions on resource allocation and process improvements. The proposed model combines the strengths of FFMEA, FDEMATEL, FAHP, and FTOPSIS to overcome the limitations of traditional approaches and provide a comprehensive method for identifying, analyzing, and justifying the critical failure modes.

7. Future Scope and Limitations

The proposed combined fuzzy model is deliberate to be mountable, making it appropriate in bigger than the current medium-scale automobile manufacturing situation. Every stage of the model pays consistent fuzzy calculation and normalization steps, assembly it scalable for application on higher datasets and various manufacturing settings. From an industrial scalability point of view, the model can be applied to industries such as electronics, chemical processing, and precision manufacturing where system reliability, safety, and process consistency are supreme. The basic reasoning of failure mode identification, weighting, and arranging stays the same while sector-specific customization is required only in input parameters, such as criteria and linguistic variables. Future research could explore integration with machine learning or IoT for real-time failure prediction and expand the criteria to include environmental and regulatory factors.

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Shankha Ghosh: Conceptualization, Methodology, Investigation, Formal analysis, Validation, Writing – Original Draft, Review & Editing. Partha Sarathi Chakraborty: Supervision, Validation. S. Nallusamy: Supervision, Validation. M. Rajaram Narayanan: Supervision, Validation. All authors have read and agreed to the published version of the manuscript.

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The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

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