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(Research Paper)

Developing a Risk Management Structure Using Combined ANP and FMEA Methods in the Machine-Made Carpet Industry

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Abstract

Producing defect-free products remains a major challenge in manufacturing industries due to complex operational risks. This study proposes a hybrid FMEA–ANP framework to improve the accuracy of risk assessment in the machine-made carpet industry. First, potential failure modes, their causes, and effects were identified using standard FMEA worksheets based on expert opinions from a large carpet factory in Kashan, Iran. Next, four main risk categories and 14 sub-risks were analysed. The Analytic Network Process (ANP), implemented in Super Decisions software, was applied to determine the relative importance of severity, occurrence, and detection criteria and to calculate weighted Risk Priority Numbers (RPNs). The results indicate that the most critical failure mode is the improper weaving of adjacent threads, followed by warp thread displacement, with both risks primarily concentrated in the weaving and spinning departments. Compared to conventional FMEA, the proposed approach provides a more realistic prioritisation of risks by accounting for interdependencies among evaluation criteria. The findings support managers in allocating resources more efficiently, reducing rework, and improving product quality. The study also highlights the applicability of the hybrid

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FMEA–ANP framework as a practical decision-support tool for risk management in manufacturing systems with complex process interactions.

Keywords: Decision Making, Risk assessment, FMEA technique, FMEA-ANP technique, The machine-made carpet industry

1. Introduction

Ensuring the quality of products and services has become one of the fundamental challenges faced by contemporary organisations and manufacturing industries. The increasing uncertainty and complexity of industrial environments have intensified the need for structured risk management practices to maintain competitiveness and enhance organisational resilience. Among the various available tools, Failure Mode and Effects Analysis (FMEA) has long been recognised as one of the most practical and powerful techniques for identifying potential failures, analysing their causes and consequences, and prioritising corrective actions. Nevertheless, the classical FMEA approach, which relies on the risk priority number (RPN) calculated as the simple product of severity, occurrence, and detection indices, has been criticised for several shortcomings. The equal weighting of these parameters, the assumption of independence among risk factors, and the frequent occurrence of tied or unstable rankings limit its effectiveness in complex, interdependent processes. To overcome these limitations, researchers have increasingly turned to hybrid approaches that combine FMEA with multi-criteria decision-making (MCDM) methods. In this regard, the ANP has been recognised as a particularly suitable complement, since it allows for the derivation of context-specific and non-equal weights for evaluation criteria, while also accounting for interdependencies and feedback relationships among factors. The integration of ANP with FMEA (hereafter referred to as FMEA-ANP), therefore, provides a more coherent and flexible structure for risk assessment, enabling more discriminative prioritisation and better alignment with systemic industrial conditions.

The machine-made carpet industry provides an appropriate and novel context for applying such an integrated approach. This sector involves highly interdependent processes, including spinning, weaving, finishing, and technical operations, in which the simplistic assumptions of equal weighting and parameter independence embedded in classical FMEA may lead to misleading risk evaluations and suboptimal managerial decisions. A review of the existing literature indicates that, despite the widespread use of FMEA across various manufacturing sectors, its application in the machine-made carpet industry remains limited and, where present, typically relies on the conventional methodology without accounting for interdependencies or unequal parameter weights. This observation reveals a clear gap in the literature, namely, the lack of comprehensive risk assessment models that integrate systemic interactions and derive more accurate, context-sensitive prioritisation schemes for this specific industry.

In light of this gap, the present research seeks to explore whether and how the integration of ANP into the FMEA framework can reshape risk prioritisation in the machine-made carpet industry. More specifically, this study investigates the dominant failure modes and root causes across the main stages of production, examines how ANP-derived weights for severity, occurrence, and detection affect prioritisation compared to the classical RPN, and evaluates the extent to which modelling interdependencies among failure factors alters managerial insights and recommended corrective actions. By addressing these questions, the study contributes in two main ways: it develops and validates an FMEA-ANP framework that explicitly accounts for interdependencies and non-equal weightings, and it applies this framework to a real-world case study in the machine-made carpet industry, thereby providing evidence of its practical utility for enhancing reliability and quality performance.

2. Literature review

2.1 FMEA and its applications

Failure Mode and Effects Analysis (FMEA) has been extensively applied as a systematic approach to identifying potential failures, evaluating their consequences, and prioritising preventive or corrective measures. In the automotive sector, for example, Ramere and Laseinde (2021) employed FMEA to optimise condition-based maintenance strategies and thereby reduce unexpected breakdowns in production lines. Similarly, Yousefi et al. (2018) applied a DEA-FMEA approach to prioritise HSE risks in an automotive parts company in Iran, adding cost and treatment duration parameters to traditional severity, occurrence, and detection indices, which led to more reliable prioritisation compared to classical FMEA. In healthcare services, FMEA has been used to improve patient safety; Teklewold et al. (2021) outlined how the method could reduce COVID-19 transmission risks in emergency departments, while Zare et al. (2018) utilised ANP in combination with FMEA to assess shift work disorders, showing that night shifts had the greatest negative impact. Mascia et al. (2020) further demonstrated that FMEA can serve as a performance improvement tool even in non-regulated biomedical research processes by guiding improvements in laboratory operations such as staff training and equipment management. These studies confirm the adaptability of FMEA across industries and suggest its potential relevance for complex and partially standardised sectors such as carpet production.

2.2 Hybrid FMEA approaches

The limitations of the traditional Risk Priority Number (RPN), particularly the equal weighting of severity, occurrence, and detection indicators, have motivated scholars to develop hybrid FMEA models. Behnia et al. (2023) combined FMEA with Goal Programming to determine cost-effective maintenance strategies in the paper industry, concluding that predictive and preventive approaches are superior to corrective ones. Other researchers have focused on handling uncertainty through fuzzy or grey theory; for instance, Resende et al. (2024) compared fuzzy FMEA with the classical approach in the aeronautical sector and showed that the fuzzy variant offered consistent yet more robust prioritisation. Lo and Liou (2018) incorporated multi-criteria decision-making and grey theory into FMEA, integrating cost and best–worst scenarios into RPN evaluation. Further extensions include Carpitella et al. (2025), who embedded Bayesian Networks into FMECA to capture causal dependencies, and Liu et al. (2024), who developed an expert-clustering and regret-theory-based FMEA model to enhance group decision-making. Moreover, the combination of FMEA with other MCDM approaches such as DEMATEL, AHP, TOPSIS, BWM, and LFPP has been widely reported in recent years (Agnusdei et al., 2023; Chukwuma et al., 2021; Daimi & Rebai, 2023; He et al., 2023; Magableh & Mistarihi, 2022; Menon & Ravi, 2021; Mubarik et al., 2021; Ouyang et al., 2022; Peddi et al., 2023; Yu et al., 2023). Collectively, these studies highlight that hybridisation significantly enhances the discriminatory power and reliability of FMEA.

2.3 ANP-based decision-making in risk assessment

The Analytic Network Process (ANP) has emerged as a powerful method for addressing interdependencies among decision criteria, and its application in risk assessment has become increasingly widespread. Kheybari et al. (2020) conducted a comprehensive review of 456 ANP applications across diverse fields such as health and safety, water management, supply chains, and energy, showing the method's breadth. Olmedo-Navarro et al. (2023) applied fuzzy ANP for managerial decision-making in SMEs, translating qualitative data into quantitative insights. Dahri et al. (2022) integrated ANP with Artificial Neural Networks and GIS to identify flood-prone areas, while Selerio Jr. et al. (2022) combined ANP with FDEMATEL to analyse the role of social media in disaster preparedness during the COVID-19 pandemic. In the context of integrating ANP with FMEA, Zhang et al. (2022) proposed an advanced PLTS-based ANP-FMEA framework that decomposes the three main FMEA parameters into sub-criteria and assigns weights through pairwise comparisons. While their approach offers fine-grained prioritisation, it increases methodological complexity. In contrast, the present research adopts classical ANP, implemented in *Super Decisions* software, to directly weight severity, occurrence, and detection in a transparent and practical way that better suits industrial practitioners.

2.4 Applications in specific industries

The integration of FMEA with decision-making tools has been successfully adapted to various industries. In finance and emerging technologies, Kirişci (2025) employed MCDM methods, including DEMATEL, AHP, and TOPSIS, to evaluate decentralised finance risks, providing insights for policymakers and industry actors. In the aeronautics sector, Resende et al. (2024) showed the consistency of fuzzy FMEA with traditional methods in prioritising high-risk effects, while in the paper industry, Behnia et al. (2023) highlighted the superiority of predictive maintenance strategies. In healthcare, Teklewold et al. (2021) and Zare et al. (2018) demonstrated the use of FMEA and ANP for patient safety and occupational risk management. The automotive industry has also been an active area, with studies by Ramere and Laseinde (2021) and Yousefi et al. (2018) confirming FMEA's utility in maintenance and HSE prioritisation. Moreover, Kar and Rai (2025) examined risk factors contributing to defects under the Quality 4.0 paradigm, emphasising the role of modernised risk-assessment frameworks in improving manufacturing quality. Collectively, these studies illustrate that structured risk assessment models are effective across industrial contexts, while also stressing the importance of contextual adaptation.

2.5 Research gap in the carpet industry

Despite the wide application of FMEA, ANP, and their hybrids across sectors, little research has directly addressed the machine-made carpet industry. Most prior works on textiles and related sectors have either relied on traditional FMEA without considering interdependencies among risk factors or have adopted generalised weighting schemes that fail to capture the realities of carpet production. Given that Iran is a global leader in carpet manufacturing and that machinery breakdowns incur high costs in terms of both production time and resource waste, this lack of targeted research is a significant gap. Building upon the flexibility of FMEA demonstrated by Mascia et al. (2020) and the methodological innovations of Zhang et al. (2022), the present study applies the FMEA–ANP hybrid approach specifically to carpet production. By identifying risks across spinning, weaving, finishing, and technical processes, and by weighting severity, occurrence, and detection through ANP in *Super Decisions* software, this research provides quantitative RPN values tailored to carpet manufacturing. The resulting framework offers both theoretical advancement and practical guidance for managers seeking to prioritise corrective actions and reduce disruptions in this economically important sector.

3. Research methodology

The traditional FMEA method, while widely used, has the limitation of neglecting the interrelationships among risks, which can significantly influence the overall risk assessment process. On the other hand, the ANP is highly effective in identifying and incorporating the interactions among decision criteria. Combining these two methods leverages the strengths of both approaches, resulting in a more accurate and reliable risk analysis framework. To further clarify the methodological approach, a flowchart of the research workflow is presented in Figure 1. This diagram outlines the sequence of steps followed in the study, from process mapping and expert data collection, through FMEA implementation and ANP modelling, to the derivation of weighted RPNs, prioritisation of risks, and formulation of corrective actions. Accordingly, in this section, the integrated FMEA-ANP methodology is introduced in detail and subsequently applied to the case of machine-made carpet production.

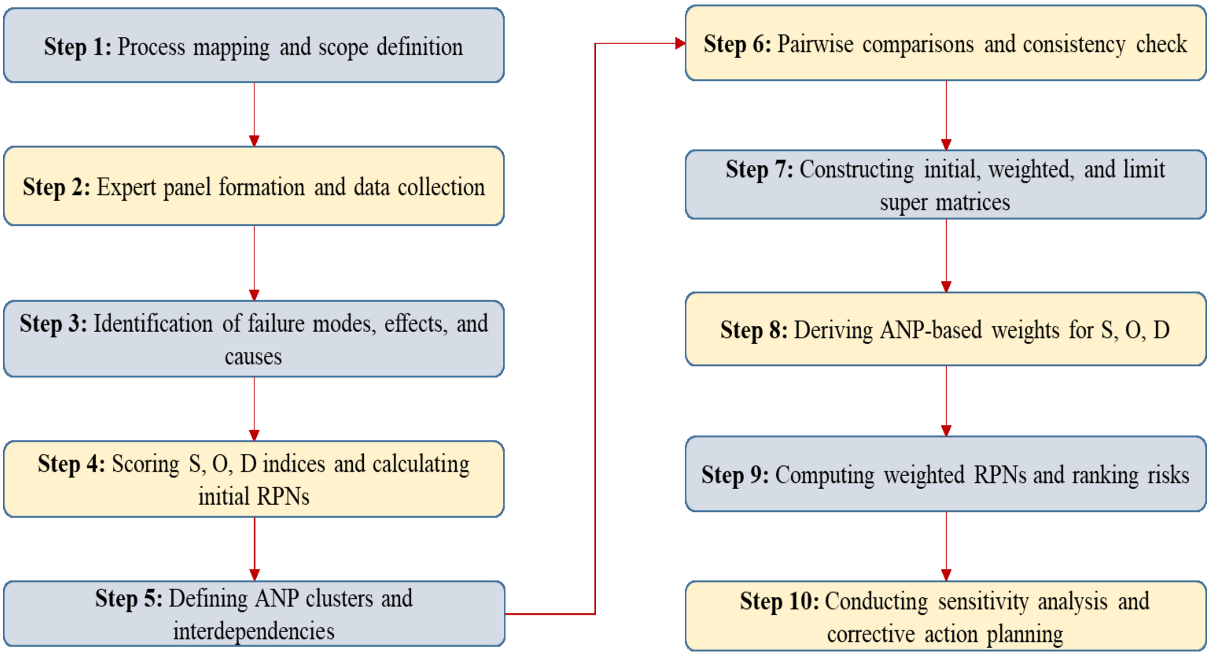

Fig. 1. Research workflow

3.1 Implementation of the FMEA method

Generally, the FMEA method consists of two steps. At first, the identification of potential failure modes and their effects is considered. The second step involves analysing the severity of the failure mode, which is done through the assessment and ranking of the criticality level of each failure. Table 1 illustrates the four risk domains and their potential risks of a considered case study.

Table 2 presents the assigned scores for occurrence, severity, and detection factors for each of the risks. The calculations of the RPN scores are also provided in the last column of the table. As mentioned earlier, the higher the score, the more significant the examined risk, requiring greater attention and preventive measures before its occurrence, significantly reduces the financial challenges imposed on the organisation. However, the obtained number alone does not have a meaningful interpretation. Instead, it should be compared with other numbers and then the results should be arranged in descending order of RPN. Risks with the highest RPN have a significant negative impact and are likely to occur frequently.

Table 1. Potential risks in the machine-made carpet industry

No.	Group	Risk area	Potential risks	Indicator
1	MCS[1]	The possibility of failure in the machine carpet spinning	Displacement of two adjacent warp threads	R1
			Not weaving two or more adjacent threads	R2
			Loosening of weft threads	R3
			Tearing apart the weft threads	R4
2	MCW[2]	The possibility of failure in machine carpet weaving	Header knotting in weave	B1
			Knitting at the edge and corners	B2
			Inappropriate carpet lifting by the roller of the weaving machine	B3
			The weaving together of two weft threads	B4
			Low height of a part of the weft threads	B5
3	MCF[3]	The possibility of failure in finishing	Carpet tearing at the back during carpet cleaning	TC
4	TA[4]	The possibility of failure due to technical aspects	Carpet fluffing	F1
			Breaking of the weft threads	F2
			Weaving the warp thread with the weft thread	F3
			Burnt weft thread	F4

Table 2. The occurrence, severity, and detection levels of each risk and the RPN scores

Risk area	Potential risks	O	S	D	RPN
The possibility of failure in the machine carpet spinning	Displacement of two adjacent warp threads	10	9	7	630
	Not weaving two or more adjacent threads	10	10	9	900
	Loosening of weft threads	4	6	8	192
	Tearing apart the weft threads	8	8	7	448
The possibility of failure in machine carpet weaving	Header knotting in weave	5	8	9	360
	Knitting at the edge and corners	4	9	10	360
	Inappropriate carpet lifting by the roller of the weaving machine	1	9	9	81
	The weaving together of two weft threads	5	9	6	270
	Low height of a part of the weft threads	3	8	10	240
The possibility of failure in finishing	The carpet is tearing at the back during carpet cleaning	6	7	5	210
The possibility of failure due to technical aspects	Carpet fluffing	7	8	7	392
	Breaking of the weft threads	2	9	10	180
	Weaving the warp thread with the weft thread	1	9	10	90
	Burnt weft thread	1	8	9	72

Table (3) categorises and ranks each of the potential. For the purpose of risk classification in this table, risks were categorized based on their RPN values: risks with RPN between 241 and 1000 were designated as Intolerable Risks; risks with RPN between 181 and 240 were considered High Risks; risks with RPN between 121 and 180 were treated as Medium Risks; risks with RPN between 61 and 120 were identified as Tolerable Risks; and finally, risks with RPN between 1 and 60 were classified as Minor Risks.

[1] Machine-made carpet spinning
[2] Machine-made Carpet Weaving
[3] Machine-made Carpet Finishing
[4] Technical Aspects

Table 3. Classification and ranking of potential risks

Potential risks	Class	Rank
Not weaving two or more adjacent threads	Intolerable	1
Displacement of two adjacent warp threads	Intolerable	2
Tearing apart the weft threads	Intolerable	3
Carpet fluffing	Intolerable	4
Header knotting in weave	Intolerable	5
Knitting at the edge and corners	Intolerable	6
The weaving together of two weft threads	Intolerable	7
Low height of a part of the weft threads	High	8
Carpet tearing at the back during carpet cleaning	High	9
Loosening of weft threads	High	10
Breaking of the weft threads	Medium	11
Weaving the warp thread with the weft thread	Tolerable	12
Inappropriate carpet lifting by the roller of the weaving machine	Tolerable	13
Burnt weft thread	Tolerable	14

As evident from Table 3, there are 7 potential risks with the highest likelihood of occurrence. Based on the obtained results, it is imperative for managers to take action to address the respective challenges and issues. Indeed, as expected, sufficient attention must be paid to the carpet manufacturing process from the outset, which is the weaving domain, in order to reduce initial risks and subsequently encounter fewer hazards throughout the production process.

3.2 The Analytic Network Process (ANP)

The Analytic Network Process (ANP) is a multi-criteria decision-making method used to determine the weights of criteria and select the optimal option based on pairwise comparisons. ANP is a more general form of the Analytic Hierarchy Process (AHP), but does not require its hierarchical structure. As a result, it represents more complex relationships between different decision levels in a network and considers interactions and feedback among criteria and options. To implement and conduct the ANP method, the following steps must be executed sequentially.

Step 1: Constructing the Research Network Diagram

In this step, the problem should be divided into criterion levels and, if applicable, sub-criteria and options, and the relationships between them should be determined.

Step 2: Forming the Pairwise Comparison Matrix

In this step, elements of each level are pairwise compared with each other, and pairwise comparison matrices are formed. Additionally, pairwise comparisons of internal relationships must also be made.

Step 3: Calculating the Inconsistency Ratio

In this step, the inconsistency ratio of the ANP is calculated. If this ratio is less than 0.1, it indicates the compatibility of the matrix.

Step 4: Forming the Initial Super matrix

Using the weights obtained from pairwise comparisons, the initial super matrix is formed. The initial super matrix is essentially the same as the weights obtained in Step 2 from pairwise comparisons. The super matrix is used to represent the flow of influence from one cluster to another cluster (external relationships) or within its own elements (internal relationships), which is achieved by exponentiating the super matrix to obtain the weight vectors. Assume that the problem has N clusters named C1, C2, ..., CN, and in the ith cluster, there are Ni elements. Now, if we select two clusters i and j and compare all elements of cluster i pairwise with the first element of cluster j, we obtain the pairwise comparison matrix shown below. This matrix represents the pairwise comparison of all elements of branch i with the first element of branch j.

$$D = \begin{array}{c} i_1 \\ i_2 \\ \vdots \\ i_{ni} \end{array} \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{ni,1} & a_{ni,2} & \cdots & a_{ni,ni} \end{bmatrix} = \begin{bmatrix} W_{i_1}^{j1} \\ W_{i_2}^{j1} \\ \vdots \\ W_{i_{ni}}^{j1} \end{bmatrix}$$

The eigenvector resulting from this pairwise comparison is defined such that if the pairwise comparison is not significant, the corresponding eigenvector will be zero. If all elements of i are compared pairwise with all elements of j, and the respective eigenvectors are obtained, the following matrix will be given:

$$W_{ij} = \begin{bmatrix} W_{i1}^{j1} & W_{i1}^{j2} & \cdots & W_{i1}^{jn} \\ W_{i2}^{j1} & W_{i2}^{j2} & \cdots & W_{i2}^{j1} \\ \vdots & \vdots & \vdots & \vdots \\ W_{in}^{j1} & W_{in}^{j2} & \cdots & W_{in}^{jn} \end{bmatrix}$$

If the above matrix is calculated for all indices, the following matrix will ultimately be obtained, which is called the super matrix.

$$D = \begin{array}{c c} & \begin{array}{ccccccc} C_1 & \cdots & C_n & A_1 & \cdots & A_n \end{array} \\ \begin{array}{c} C_1 \\ \vdots \\ C_n \\ A_1 \\ \vdots \\ A_n \end{array} & \begin{bmatrix} 0 & \cdots & 0 & w_{1,n+1} & \cdots & w_{1,n+m} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & 0 & w_{n,n+1} & \cdots & w_{n,n+m} \\ w_{n+1,1} & \vdots & w_{n+1,n} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ w_{n+m,1} & \vdots & w_{n+m,n} & 0 & \cdots & 0 \end{bmatrix} \end{array}$$

Matrix of pairwise comparisons of criteria based on options

Matrix of pairwise comparisons of criteria based on criteria

Step 5: Creating a Weighted Super matrix

After creating the initial super matrix, the weighted super matrix should be established.

Step 6: Creating the Limit Super matrix

The weighted super matrix needs to be raised to an infinite power to converge each row to a consistent number, representing the weight of each criterion, sub-criterion, or option.

To conduct network analysis, first, the elements of each cluster, the relationships between clusters, and the internal relationships of all elements must be compared. The resulting matrices from each calculation are placed side by side to form a super matrix. Using the normalisation concept, the non-normal super matrix is transformed into a normalised super matrix. In the normalised super matrix, the sum of all column elements equals one. The normalised super matrix is extracted from the Super Decision software. Finally, the limit super matrix is calculated. The limit super matrix is obtained by raising all elements of the normalised super matrix to the power of infinity. This process is repeated until all elements of the super matrix become similar. In this case, all elements of the super matrix will be zero, and only the elements related to the sub-criteria will have a value that repeats in all rows related to that element. The calculated limit super matrix can provide the final priority of the criteria and alternatives.

3.3 The FMEA-ANP method

The FMEA-ANP approach integrates the common steps of the FMEA and ANP methods, with the distinguishing feature being the consideration of the interrelationships between parameters in FMEA, namely severity, occurrence, and detection, in the form of a network. The proposed method is as follows.

Step 1. Data Collection of the Process

In the FMEA-ANP method, data gathering and evaluations are conducted in the form of a group of experts. This group obtains the initial fundamental mindset using product engineering maps or flowcharts of operations.

Step 2. Identification of Potential Failure Modes

After gaining a correct understanding of the phenomenon under investigation, the group members brainstorm potential failure patterns that threaten the industrial process or the quality of the product or service. These discussions involve a collective exchange of ideas and thoughts. A failure pattern or mode represents the failure of a specific component of the phenomenon under investigation to perform expected tasks.

Step 3. Determine the potential effects of failure

By listing the potential failure modes, the group members review them to identify their potential consequences if they occur. It's possible that some failures may result in multiple adverse effects.

Step 4. Diagnosing the causes of each failure

After identifying the potential failure modes and determining their potential effects, the causes of each failure are investigated through team brainstorming. This is a list of possible contributing factors to each failure.

Step 5. Determining the degree of parameters for each potential cause of failure

By using a standard comparison, members of the FMEA team match their experiences with a range of possible severity, occurrence, and detection parameter ratings (from one to ten), assigning specific numbers to each potential failure mode for each parameter. These numbers specify the level of risk associated with each potential cause.

Step 6. Model Construction

In the FMEA-ANP method, FMEA parameters are interconnected in the form of a network; there is a mutual relationship among the causes of failure occurrences. The objective of this model is to determine the weight and priority of severity, occurrence, and detection parameters based on their level of riskiness. The model is constructed in three levels, including goal, criteria and parameters.

Step 7. Regulating interdependencies and performing pairwise comparisons between clusters

What justifies the integration of network analysis and failure analysis is the presence of mutual interactions among potential failure factors. Besides the existence of influences among potential failure patterns, the potential failure factors within their own patterns or across different failure patterns create interconnections and mutual dependencies. If a failure factor affects another factor within the same failure pattern, this is an internal dependency. However, if a potential failure factor from one failure pattern affects another one from a different pattern, this is an external relationship, establishing connections between failure clusters. To organise these mutual dependencies, a matrix of clusters (patterns or failure modes) and their elements (failure factors) is formed. If there is a relationship between elements (in corresponding positions in the matrix), the value one is assigned, zero is assigned. After identifying the relationships and dependencies in the previous step, pairwise comparisons among clusters, elements, and alternatives are conducted.

Step 8. Forming the super matrix and calculating the weight of the parameters

To obtain the normalised super matrix, the blocks of the non-normalised super matrix (clusters of failure modes and parameters) are multiplied by the priority of their respective cluster (resulting from pairwise comparisons of clusters in the model). In this matrix, the sum of the columns is equal to one. The resulting super matrix is raised to a high power until further increasing the power does not significantly change the components of the matrix. At this point, the final matrix has been obtained.

In the FMEA-ANP method, weights are assigned to parameters in such a way that, regardless of their individual values, they sum up to 3. To achieve this, the following normalisation formula is used to normalise the elements of the parameter block in the final super matrix and obtain the weights:

$$w_i = \frac{3 \times a_i}{\sum a_i} \tag{1}$$

Where w_i is the normalised weight for parameter i, a_i is the original weight for parameter i and i is the respective parameter.

Step 9. Calculation of RPN for each identified factor

In order to calculate the RPN, three factors of severity, occurrence, and detection must be multiplied together, taking into account the same degree of importance and weight for each of them. The standard equation is presented below.

$$(RPN) = Severity\ (S) \times Occurence\ (O) \times Detection\ (D) \tag{2}$$

In the proposed FMEA-ANP method, the assumption of having different weights for each of the parameters is considered as follows. The weights of severity, occurrence, and detection parameters previously calculated are incorporated into this equation as the power of each respective parameter to calculate the risk priority score.

$$RPN : S^{\alpha} \times D^{\gamma} \times O^{\beta} \tag{3}$$

Step 10. Take corrective actions

Corrective actions are taken to eliminate or reduce potential high-risk failure modes. To achieve this goal, systematic problem-solving methods are employed. The optimal way of optimisation is to reduce the likelihood of failure occurrence, as reducing this probability will also decrease the need for inspection methods.

4. Case study and findings

In this section, considering the group scoring assigned to each of the parameters, the FMEA-ANP model was implemented in the machine-made carpet industry and designed in the Super Decisions software. The main objective of this model is to determine the weight and priority of risk for respective parameters.

4.1 Model construction

First, the model related to the internal relationships of each criterion (main risk areas), sub-criteria (sub-risks), and options (severity, occurrence, and detection) was designed at three levels, as shown in Figure 2.

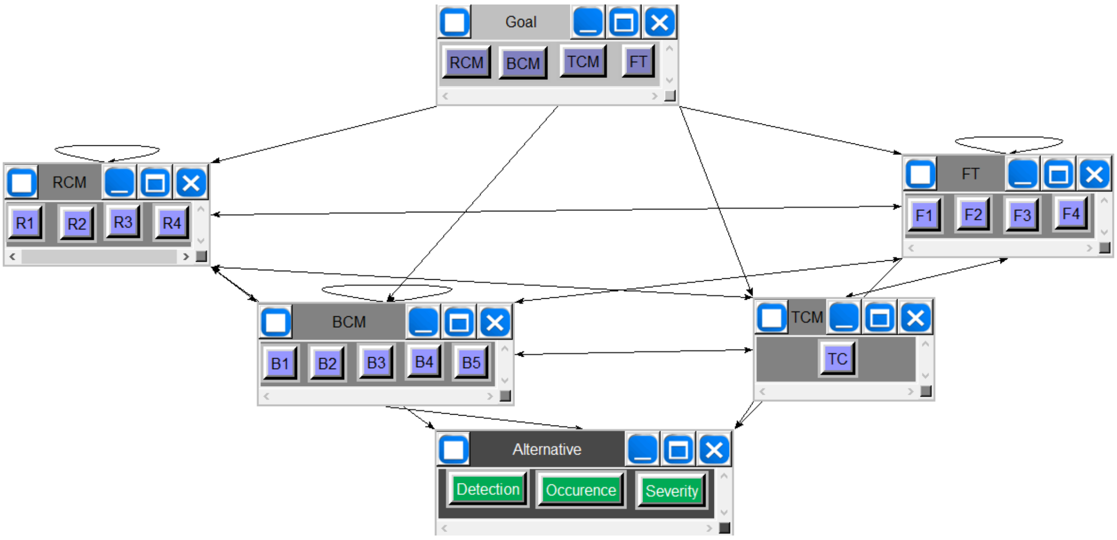

Fig. 2. The structure of the decision options model

In which the objective level clarifies the priority of risk for three parameters. At the second level, failure clusters form the criteria of the model. Each potential failure mode represents a failure cluster. Therefore, in this model, there are four failure clusters: Machine-made Carpet Spinning (MCS/RCM), Machine-made Carpet Weaving (MCW/BCM), Machine-made Carpet Finishing (MCF/TCM), and Technical Aspects (TA/FT). These clusters, along with their elements at the second level, can be observed in Figure 2. Finally, the third level pertains to the parameters of the model.

4.2 Regulating interdependencies and performing pairwise comparisons between clusters

In this step, various dependencies and comparisons in the sample under investigation are examined. Identification of dependencies and pairwise comparisons has been conducted by experts.

4.2.1. Expert team formation and data collection

The expert team consisted of eight key specialists from the machine-made carpet industry. Their expertise included: one Production Manager, two Quality Control Engineers, two Industrial Engineers specialising in quality and risk systems, and three experienced supervisors from the weaving and spinning lines. On average, these experts had over 10 years of specialised experience in their respective fields. The data for pairwise comparisons were obtained by geometric aggregation of the eight experts' opinions.

4.2.2. Network structure and pairwise comparison validation

After designing the network structure (Figure 2), the pairwise comparison matrices were completed using the geometric mean of the expert team's judgments. The nine-point Saaty Scale was used for this purpose. To validate the consistency of the judgments, all pairwise comparison matrices were checked for their Inconsistency Ratio (IR). Only matrices with an IR less than 0.1 were accepted for final calculations. For instance, the Inconsistency Ratio for the main criteria comparison matrix was reported as 0.051, indicating a high level of consistency in expert judgments.

4.2.3. Calculation of final weights and weighted RPN

A) Final Weight Calculation (W): The final weights for the criteria (Severity, Occurrence, and Detection) were calculated using the Limit Super matrix in the Super Decisions software. These weights reflect the relative importance of the criteria, considering the interdependencies within the network structure. The calculated final weights are: $W_S(\text{everity}) = 0.48,\quad (\text{WOccurrence}) = 0.33,\ \ W_D(\text{Detection}) = 0.19.$

B) Converting Weights to Exponents and the Weighted RPN Formula: In the ANP-weighted FMEA model, the final weights (W) are utilised as exponents (powers) in the Weighted Risk Priority Number (WRPN) formula. This non-linear approach grants greater influence to criteria with higher weights (such as Severity), providing a more realistic risk ranking. The WRPN formula is defined as: $WRPN = S^{W_S} \times O^{W_O} \times D^{W_D}$. Where S, O, and D are the traditional FMEA scores (1 to 10), and W_S, W_O, and W_D are the final ANP weights.

C) Numerical Example: To clarify the process, consider the failure mode "Not weaving two or more adjacent threads" as the most critical risk. Its traditional FMEA scores are: S=10, O=9, and D=10. The Weighted RPN (WRPN) is calculated as follows: $WRPN = 10^{0.48} \times 9^{0.33} \times 10^{0.19} \approx 9.59$. This value (9.59) is the final index used for risk prioritisation, reflecting the high importance of the Severity criterion (with an exponent of 0.48) in the final calculation.

4.3 Forming the super matrix and calculating the weight of the parameters

In this step, the following calculations are performed to form the super matrix.

a) Formation of the non-normalised super matrix: Initially, the non-normalised super matrix is formed. The rows and columns of this matrix represent the clusters and their corresponding elements. The elements of this matrix indicate the weight of the element corresponding to the row with respect to the element corresponding to the column. This super matrix needs to be normalised.
b) Formation of the normalised super matrix: In this step, the non-normalised super matrix is transformed into a normalised super matrix. For this purpose, the elements of each block in the non-normalised super matrix are multiplied by the weight of that block. In the normalised super matrix, the sum of each column will be equal to one.
c) Formation of the final super matrix: The obtained super matrix in the previous step is raised to a high power until there is no significant change in the matrix components with increasing power. In this state, the final matrix is obtained, which is shown in Table 4. In

the usual case, the power of each parameter in the FMEA method is equal to one; that is, the sum of the powers of the parameters will be 3. In the FMEA-ANP method, weights are assigned to parameters in such a way that regardless of their individual values, the sum of the weights is equal to 3.

Table 4. The final matrix

		Parameter			Criteria				MCS				MCW					MCF	TR			
		D	S	O	MCS	MCW	MCF	TR	R1	R2	R3	R4	B1	B2	B3	B4	B5	TC	F1	F2	F3	F4
Parameter	D	0	0	0	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077
	S	0	0	0	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047	0.047
	O	0	0	0	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088
Criteria	MCS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	MCW	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	MCF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MCS	R1	0	0	0	0.0687	0.0687	0.0687	0.0687	0.0687	0.0687	0.0687	0.0687	0.0687	0.0687	0.0687	0.0687	0.0687	0.0687	0.0687	0.0687	0.0687	0.0687
	R2	0	0	0	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013
	R3	0	0	0	0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032
	R4	0	0	0	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054
MCW	B1	0	0	0	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045	0.045
	B2	0	0	0	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065
	B3	0	0	0	0.0657	0.0657	0.0657	0.0657	0.0657	0.0657	0.0657	0.0657	0.0657	0.0657	0.0657	0.0657	0.0657	0.0657	0.0657	0.0657	0.0657	0.0657
	B4	0	0	0	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082
	B5	0	0	0	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078
MCF	TC	0	0	0	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023
TR	F1	0	0	0	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043

	F2	F3	F4
Parameter	0	0	0
	0	0	0
	0	0	0
Criteria	0.115	0.034	0.063
	0.115	0.034	0.063
	0.115	0.034	0.063
	0.115	0.034	0.063
MCS	0.115	0.034	0.063
	0.115	0.034	0.063
	0.115	0.034	0.063
	0.115	0.034	0.063
MCW	0.115	0.034	0.063
	0.115	0.034	0.063
	0.115	0.034	0.063
	0.115	0.034	0.063
	0.115	0.034	0.063
MCF	0.115	0.034	0.063
TR	0.115	0.034	0.063
	0.115	0.034	0.063
	0.115	0.034	0.063
	0.115	0.034	0.063

d) Formation of the clusters' weighted matrix: After forming the final matrix, the weighted cluster matrix is created, as presented in Table 5.

Table 5. The weighted cluster matrix

	Parameters	Criteria	MCS	MCW	MCF	TA
Parameters	0	0	0.2	0.2	0.25	0.2
Criteria	0	0	0	0	0	0
MCS	0	0.724	0.2	0.2	0.25	0.2
MCW	0	0.135	0.2	0.2	0.25	0.2
MCF	0	0.054	0.2	0.2	0	0.2
TA	0	0.085	0.2	0.2	0.25	0.2

e) Formation of parameter weights matrix: Based on the obtained matrix in Table 5, un-normalised weights for parameters are obtained. Using the correction formula, the weights of parameters are calculated, as shown in Table 6.

Table 6. Weight of parameters

Num	Parameters	Unnormalized weight	Correction weight
1	Detection	0.0775	1.088
2	Severity	0.0475	0.667
3	Occurrence	0.0885	1.243

4.4 Calculation of RPN for each identified factor

Finally, the RPN score is calculated for each of the identified factors. For this purpose, the degree of severity, occurrence, and detection parameters are used to calculate the RPN score using the following formula. The results of the calculations are shown in Table 7.

As shown in Table 7, the RPN values obtained from the FMEA-ANP method are smaller than those obtained from FMEA. This indicates that when proper weights are applied to each parameter, their risk severity may be lower than initially perceived. This implies that sometimes, taking corrective action on one parameter to achieve a lower risk level prevents the need for additional corrective measures on other parameters with lower risk susceptibility. Furthermore, as depicted in the fifth column of Table 7, two sub-risks, "header knotting in weave "and "knotting at the edge and corner", are placed in the same priority. However, according to the production experts, the first risk is considered to be more important than the second risk as reflected in the RPN obtained for the FMEA-ANP method. Based on the cluster matrix, machine-made carpet spinning and then carpet weaving were identified as the most significant potential causes of risk, with the jacquard system malfunctions identified as the most critical potential risk factor. The second most significant risk factor is wrong threading or changing the bobbin. Carpet pile fluffing, failure of the cutting blade and improper cutting are the next influencing risk factors which can cause adverse performance in production.

Table 7. RPN values and priority of potential risk factors in FMEA and FMEA-ANP methods

Risk area	Potential risks	RPN		Priority	
		FMEA	FMEA-ANP	FMEA	FMEA-ANP
The possibility of failure in the machine carpet spinning	Displacement of two adjacent warp threads	630	629.428	2	2
	Not weaving two or more adjacent threads	900	887.59	1	1
	Loosening of weft threads	192	177.8	9	10
	Tearing apart the weft threads	448	440.928	3	3
The possibility of failure in machine carpet weaving	Header knotting in weave	360	323.14	5	5
	Knitting at the edge and corners	360	297.057	5	6
	Inappropriate carpet lifting by the roller of the weaving machine	81	47.281	12	13
	The weaving together of two weft threads	270	224.86	6	7
	Low height of a part of the weft threads	240	192.053	7	9
The possibility of failure in finishing	Carpet tearing at the back during carpet cleaning	210	195.61	8	8
The possibility of failure due to technical reasons	Carpet fluffing	392	373.49	4	4
	Breaking of the weft threads	180	125.504	10	11
	Weaving the warp thread with the weft thread	90	53.024	11	12
	Burnt weft thread	72	43.709	13	14

To better understand, in Figure 3, based on the results of the FMEA-ANP model, the risks are grouped into three categories: high risks, medium risks, and low risks. This grouping represents the prioritisation of corrective actions to mitigate damaging effects. In situations where budgetary or equipment limitations prevent the implementation of all corrective actions, addressing high risks will have the greatest impact on reducing potential hazards.

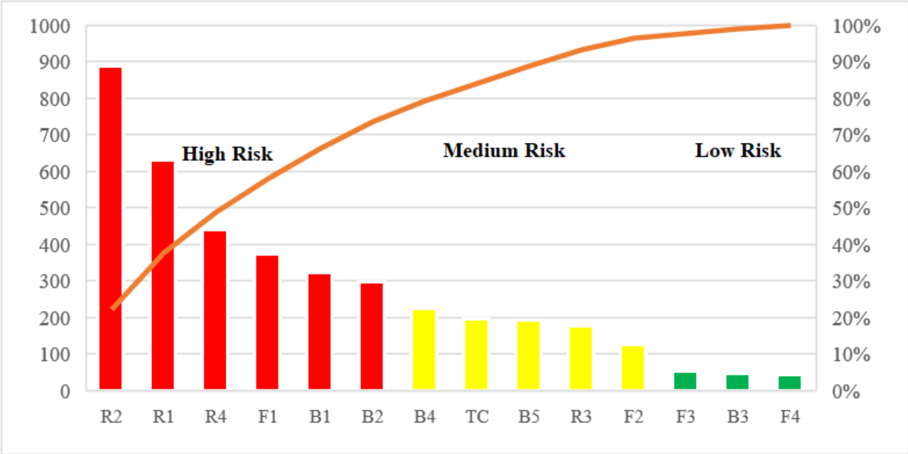

Fig. 3. Risk classification based on FMEA-ANP scores

4.5 Take corrective actions

Based on Table 7, in order to reduce the probability or consequences of the recognised high risks, corrective actions should be taken. The most important cause of malfunction in the Jacquard system is the possibility of mistakes in pattern punching due to the wear of machinery, which may lead to incorrect patterns on the produced carpet. These errors may occur because of electrical fluctuations or burning of the Jacquard board.

On the other hand, if the yarn is not of suitable quality, it may break during carpet weaving ,resulting in unevenness in the carpet texture. This is due to the insufficient saturation of the pile with liquid paraffin. Another reason is the lack of precision of the weaving machine operator when separating the warp yarn and the incorrect pulling of the pile from the warp threads. With such negligence, the pile does not get placed in its proper position, causing problems at the back of the carpet. Additionally, if there are excessive pile breakages due to collision with the mako or rapier, the carpet is considered to be of inferior quality. Therefore, corrective actions should be taken in both areas to minimise the occurrence and severity of damage in the domain of machine-made carpet weaving as much as possible.

4.6 Sensitivity analysis of risk ranking

To evaluate the stability and robustness of the results derived from the FMEA–ANP model, a sensitivity analysis was performed on the final criteria weights. In this analysis, the weight of each criterion was individually varied by $\pm 10\%$, while the weights of the other two criteria were proportionally adjusted to maintain the constraint $\sum W = 1$. The results of the sensitivity analysis indicated that despite the 10% variation in criteria weights, the ranking of the top three critical risks remained consistent across all tested scenarios. This stability confirms that the designed ANP model and the final criteria weights provide a robust and reliable risk ranking that is resistant to minor errors in expert judgment or slight uncertainties.

5. Discussion

The hybrid analysis conducted in this study shows that the most critical failure modes in machine-made carpet production concentrate in the spinning and technical clusters, with weaving-related issues, particularly Jacquard system malfunctions and errors linked to threading and bobbin changes, emerging as prominent drivers of risk. Grouping risks into high, medium, and low tiers clarifies the order in which mitigation should proceed when resources are limited, ensuring that interventions first target the few intolerable risks with the largest impact on waste, rework, and downtime. In our data, applying ANP-derived weights to FMEA parameters yields calibrated RPN values that better reflect operational reality; absolute RPNs decrease relative to the traditional method, while the ranking of the most critical items remains stable, enabling sharper prioritisation without inflating perceived severity. These patterns are consistent with expert assessments and the cluster-weight evidence from the study's super matrix and classification results.

5.1 Theoretical implications

Methodologically, the results reinforce assessment of the classic RPN’s equal-weight and independence assumptions by showing that interdependencies among severity, occurrence, and detection meaningfully shape risk salience. Embedding FMEA within an ANP network addresses these limitations by estimating criterion weights endogenously from pairwise comparisons that capture feedback and dependence, thereby producing a risk index that aligns with the systemic nature of production processes. This finding is in accordance with Zhang et al. (2022), who advocated network-based weighting of FMEA factors and finer-grained modelling of their interactions, including ANP-enhanced or PLTS-ANP variants that relax additivity and independence and improve discriminative power in ranking failure modes. It also converges with studies that extend FMEA through MCDM to incorporate contextual criteria and to stabilise rankings under real-world constraints (Kirişci, 2025; Agnusdei et al., 2023; Daimi & Rebai, 2023; He et al., 2023; Magableh & Mistarihi, 2022; Menon & Ravi, 2021; Mubarik et al., 2021; Ouyang et al., 2022; Peddi et al., 2023; Yu et al., 2023). Together, these comparisons situate FMEA-ANP as a theoretically coherent response to well-documented shortcomings of the conventional RPN and as a complementary alternative to fuzzy, DEA-, or social-network–assisted FMEA formulations reported in recent research.

5.2 Managerial implications

From a practical standpoint, the calibrated rankings indicate where managers in carpet manufacturing can achieve the greatest reliability gains per unit of effort. First, prioritise preventive and predictive measures in the high-risk spinning/technical clusters and the weaving line elements that drive Jacquard anomalies; implement systematic checks of pattern punching, institute voltage stabilisation and board-health monitoring for Jacquard control units, and schedule targeted maintenance to reduce fault propagation from minor electrical fluctuations. Second, reinforce yarn-quality gates, especially paraffin saturation and tensile integrity, before and during weaving, and standardise operator procedures for warp–weft separation and tensioning; these steps directly address frequent breakage and misplacement mechanisms observed on the floor. Third, deploy the FMEA-ANP worksheet as a living instrument; review weights and rankings quarterly with cross-functional experts, concentrate budget on the “intolerable” tier until its drivers fall to the “high” tier, and only then diffuse resources to medium-risk items. This staged approach is designed to cut scrap and rework quickly while preventing over-investment in low-leverage controls.

6. Conclusions

Effective risk assessment is indispensable in industries where tightly coupled processes and quality sensitivity determine competitiveness and operational resilience. This study developed and applied an integrated FMEA–ANP framework to the machine-made carpet production process in Kashan, systematically identifying fourteen principal risks and their root causes across spinning, weaving, finishing, and technical operations. By combining conventional FMEA worksheets with ANP-derived, interaction-aware weights for severity, occurrence, and detection, the proposed approach produced more discriminative and operationally coherent Risk Priority Numbers (RPNs). The empirical results indicate that the greatest concentration of intolerable risk lies in weaving and technical clusters, notably in Jacquard system malfunctions and incorrect yarn tensioning, suggesting that targeted preventive and corrective measures in these areas will yield the largest reductions in scrap, rework, and production interruptions. Moreover, the FMEA–ANP procedure demonstrated that appropriately calibrated parameter weights can lower overstated RPNs from classical FMEA and refine managerial focus toward the most consequential failure mechanisms.

Beyond ranking, the study offers actionable implications for practitioners: managers should prioritise investments in preventive maintenance and real-time monitoring of Jacquard controllers and drive systems, strengthen yarn-quality gating and tension-control protocols upstream of weaving, and institutionalise cross-functional reviews of weighted FMEA outcomes to ensure continuous alignment between risk rankings and operational priorities. Using the FMEA–ANP worksheet as a living decision-support tool—periodically recalibrated through expert panels—can help firms allocate limited resources more efficiently by addressing intolerable risks first and rolling forward to medium- and low-tier items as performance improves.

6.1 Research limitations and future research agenda

Several limitations qualify the generalizability of our findings and point to promising avenues for future work. First, the case-study design was confined to a single production region and a finite expert panel, which may limit external validity; multi-site replications and larger, stratified expert samples would strengthen inference and capture wider operational heterogeneity across firms and geographies. Second, the present implementation relies on cross-sectional expert judgments and does not incorporate dynamic or real-time operational data; integrating Industry 4.0 sensor streams and digital twin models with the FMEA–ANP framework would enable continuous monitoring and timely re-weighting of risks. Third, the method in its current form does not explicitly model common-cause failures or probabilistic causal propagation; future research should explore hybridisations with Bayesian networks or Markov models to represent causal dependencies and to quantify how single events may trigger cascades across clusters. Fourth, linguistic uncertainty and subjective scoring could be more rigorously addressed through fuzzy, interval-valued, or stochastic extensions of ANP, accompanied by Monte Carlo–based sensitivity and robustness analyses to test the stability of rankings under alternative assumptions. Finally, regarding generalizability, the present results are most directly applicable to process-based industries with similar characteristics to machine-made carpet manufacturing, such as textile weaving and spinning or other sectors with tightly coupled production stages. While the proposed FMEA–ANP framework is theoretically transferable, its outcomes may vary across different industrial contexts. To enhance external validity and credibility, future studies should replicate the analysis in other manufacturing sectors and validate expert-based results with field or experimental data. Such replications would clarify the specific conditions under which the proposed approach yields the most reliable outcomes and strengthen its applicability beyond the focal industry. In summary, the FMEA–ANP framework presented here advances both theoretical and practical understanding of risk prioritisation in highly interdependent manufacturing contexts and offers a transparent, adaptable procedure for managers seeking to reduce quality failures efficiently.

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