Optimising Risk Management in Wood-based Manufacturing: A Fuzzy AHP-FMEA Framework Approach

Ivana Perić,[a] Kristina Klarić,[a] Andreja Pirc Barčić,[a,*] Karla Vukman,[a] Tomislav Sedlar,[a] and Petra Grošelj[b]

This study integrates the Fuzzy Analytic Hierarchy Process (AHP) with the Failure Mode and Effects Analysis (FMEA) to enhance risk prioritisation in wood-based manufacturing. Traditional FMEA methods face challenges in handling subjective evaluations and complex environments. By incorporating fuzzy logic, this study refines the Risk Priority Number (RPN) calculation, enabling a more nuanced assessment of failure modes. Critical failure points, such as delays in order processing, production, and delivery, were identified, highlighting their impact on operational efficiency, customer satisfaction, and financial outcomes. Using the Pareto principle, it was revealed that addressing the top 20% of the identified risks could mitigate approximately 80% of the overall risk exposure. Proposed corrective measures, including enhanced employee training, streamlined workflows, and improved communication protocols, provide actionable strategies to optimise processes and ensure sustainability. Conducted within a Croatian wood-manufacturing company, this framework demonstrated its efficacy in refining risk assessments and supporting continuous improvement. The findings advance risk management methodologies and showcase the potential for broader applications in dynamic and complex industrial environments.

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*Contact information: a: University of Zagreb Faculty of Forestry and Wood Technology, 10000 Zagreb, Croatia; b: Department of Forestry and Renewable Forest Resources, Biotechnical Faculty, University of Ljubljana, 1000 Ljubljana, Slovenia; *Corresponding author: apirc@sumfak.unizg.hr*

INTRODUCTION

Evaluating organisational performance is critical for continuous advancement and long-term success (Mitrea-Curpanaru 2021). Organisations often identify performance gaps related to resources, strategies, processes, and motivation through analyses and needs assessments (Abu Dabous *et al.* 2021). Addressing these gaps requires setting measurable objectives and implementing continuous improvement technologies (Abu *et al.* 2019). Effective performance management enables organisations to adapt to evolving market demands and remain competitive (Mitrea-Curpanaru 2021; Skorupińska *et al.* 2024).

Various risk assessment methods have been developed to identify, evaluate, and mitigate potential failures in manufacturing. Some widely applied approaches include:

- Hazard and Operability Study (HAZOP): Identifies process deviations and potential hazards (Crawley *et al.* 2015).

- Fault Tree Analysis (FTA) and Event Tree Analysis (ETA): These methods use logic-based modeling to analyze failure probabilities and potential outcomes (Ericson 2015; Bedford and Cooke 2001).
- Bow-Tie Analysis: Provides a visual representation of risks and control measures (de Ruijter and Guldenmund 2016).
- Lean Six Sigma (LSS): A performance improvement approach that combines Lean principles (waste reduction) and Six Sigma techniques (variation minimization) to enhance quality (Simanová and Sujová 2022; Skorupińska *et al.* 2024).
- Multi-Criteria Decision-Making (MCDM) Methods: Used to evaluate and prioritize risks in complex decision environments (Wang *et al.* 2020; Grošelj *et al.* 2016).

Among these, Failure Mode and Effects Analysis (FMEA) has emerged as a widely recognized tool due to its structured approach to identifying and prioritizing risks in manufacturing (Kushwaha *et al.* 2020). Originally developed in the aerospace sector in the 1960s, FMEA was later adopted by the automotive industry to enhance quality and safety standards. Over time, it has been implemented across multiple industries, including manufacturing, healthcare, energy, and software, to systematically assess and mitigate potential failures (Bailey 2017; Abu *et al.* 2019; Liu *et al.* 2020; Mohammadfam and Gholamizadeh 2021; Talkhooncheh *et al.* 2021; Yang *et al.* 2024).

Despite its advantages, traditional FMEA has limitations, including subjectivity in risk evaluation, inconsistent prioritization, and a restricted numerical scale for RPN values (Liu *et al.* 2011). To address these challenges, the Analytic Hierarchy Process (AHP) has been integrated with FMEA to introduce a hierarchical structure for risk evaluation. AHP enhances risk prioritization by assigning relative weights to risk factors and using pairwise comparisons to improve decision-making accuracy (Saaty 1980). AHP has been widely applied in multiple industries. In manufacturing, AHP has been used to optimize supplier selection and resource allocation in sustainable practices (Gupta *et al.* 2015; Dweiri *et al.* 2016). Within supply chain management, it helped assess and prioritize risks, strengthening resilience (Tramarico *et al.* 2015). In the healthcare sector, AHP aided in environmentally responsible supplier selection, ensuring sustainable procurement (Schmidt *et al.* 2015). AHP was also widely used in renewable energy projects, supporting investment and site selection (Journals.sagepub.com), while in environmental risk assessment, it helped evaluate environmental impacts and guide risk mitigation strategies (Topuz and van Gestel 2016). Additionally, AHP played a role in consumer decision-making, identifying key consumer preferences in purchasing and informing marketing strategies (Oblak *et al.* 2017; Sharma and Joshi 2019). By incorporating AHP, FMEA's risk prioritization process is refined, making it a more effective tool for complex risk environments (Liu *et al.* 2015; Abdelgawad and Fayek 2010).

In the wood-based industry, production complexities and material variability require advanced risk assessment tools. FMEA systematically identifies risks and failure modes in critical processes such as drying, cutting, and finishing, enabling early intervention to reduce defects, optimize production, and support sustainability goals (Badiu *et al.* 2015; Boran and Gökler 2019; Senthilkannan and Parameshwaran 2019; Lv *et al.* 2020; Basuki *et al.* 2021; Urbina *et al.* 2022; Prasmana and Hidayat 2023; Zahra *et al.* 2024).

However, traditional FMEA struggles with uncertainties, particularly in high-variability industries such as wood manufacturing (Lo *et al.* 2018, 2019; Li *et al.* 2021; Liu *et al.* 2019). To address these challenges, a hybrid approach combining fuzzy logic and

AHP has been introduced, enabling expert-driven weight adjustments and more refined RPN calculations (Grošelj and Dolinar 2023). By incorporating fuzzy linguistic scales, this advanced framework enhances decision-making accuracy in dynamic production environments, such as wood processing (Wu *et al.* 2020; Więckowski and Sałabun 2024).

Additionally, the Pareto Principle has been applied to prioritize critical risks, thus ensuring optimized resource allocation and reduced overall risk exposure (Keskin Çıtıroğlu *et al.* 2022). This principle helps focus risk management efforts on the most significant failure modes, improving the efficiency of preventive measures.

Study Objectives

This study aims to enhance risk assessment in wood-based manufacturing by leveraging a Fuzzy AHP-FMEA approach, thereby improving risk prioritization and decision-making accuracy. The specific objectives are to:

- Identify critical failure points: Use FMEA to address high-risk areas that impact productivity, quality, and safety.
- Enhance risk prioritisation: Integrate fuzzy AHP with FMEA to manage subjective evaluations in complex environments.
- Optimize production and safety: Recommend actions to improve efficiency, reduce costs, and enhance safety.

By integrating structured risk assessment methods with continuous improvement methodologies, this study seeks to advance risk management practices in the wood-based industry, ultimately supporting sustainability and efficiency goals.

Theoretical Background: FMEA And Fuzzy AHP

Effective performance management and risk assessment are critical in wood-based manufacturing, where complex processes and variable materials pose operational challenges (Susilawati 2021). Issues such as equipment downtime, skill shortages, and material inconsistencies increase risks and reduce efficiency if not addressed (Susilawati 2021). For example, regular CNC machine maintenance in a Malaysian furniture factory reduced downtime and stabilised production. Similarly, Badiu *et al.* (2015) highlighted the role of maintenance and quality control in reclaimed wood furniture production. Risk assessment integrated with performance management enhances operational stability, as demonstrated by Kulińska and Matulewski (2022), who showed that better training and logistic planning mitigate supply chain risks.

Among the various tools used to strengthen risk assessment and operational efficiency, FMEA stands out as a systematic approach to identifying and prioritising risks through RPNs (Sartor and Cescon 2019). It has been applied in the wood manufacturing sector to reduce defects (Prasmana and Hidayat 2023), minimise waste (Suhardi *et al.* 2021), and optimise processes such as varnishing (Kholil 2024). For example, integrating FMEA with Lean Manufacturing reduced defects by 20% in Peruvian wood furniture production (Urbina *et al.* 2022). Advanced FMEA models, such as ANFIS-Taguchi (Boran and Gökler 2019) and fuzzy FMEA (Jatwa and Sukhwani 2022), further expand their capabilities for complex risk scenarios.

Despite its advantages, FMEA faces limitations such as subjective evaluations, inconsistent risk implications, and scale constraints (Liu *et al.* 2011; Li and Chen 2019). The limited range (120 unique values out of 1000) can lead to redundancy and misinterpretation (Liu *et al.* 2013; Chang *et al.* 2014). By integrating a hierarchical structure for evaluating and prioritizing risk factors, AHP reduces inconsistencies in subjective judgments, enhancing decision-making accuracy (Saaty 1980). AHP structures complex decision problems into hierarchical levels, allowing for a systematic evaluation of risk factors. Its pairwise comparison method enables experts to assess the relative importance of risks rather than assigning fixed numerical scores, reducing subjectivity (Saaty 1980). Additionally, AHP calculates weighted priorities, improving the precision of failure mode rankings based on their actual impact (Liu *et al.* 2015). The Consistency Ratio (CR) further enhances decision-making by verifying the logical coherence of expert judgments, minimizing biases (Wang *et al.* 2020).

The integration of AHP with FMEA significantly improves risk prioritization by addressing the limitations of the traditional RPN approach. While conventional FMEA assigns equal weight to severity, occurrence, and detection scores, AHP introduces customized weightings, ensuring a more precise and industry-specific risk assessment (Liu *et al.* 2015; Wang *et al.* 2020). By incorporating a hierarchical structure and weighted prioritization, the AHP-FMEA hybrid model enhances decision-making, particularly in complex industrial environments such as wood-based manufacturing, where risks stem from material variability, equipment reliability, and supply chain disruptions.

To further overcome the limitations of FMEA, fuzzy logic can be used together with AHP and FMEA to increase the reliability of expert judgement by reflecting the way humans naturally think and make decisions. Fuzzy logic was developed by Zadeh (1965) to deal with uncertainties and ambiguities that often occur in real-life situations. Compared to classical logic, which relies on binary true-or-false values, fuzzy logic allows for partial truths, which increases its flexibility and makes it particularly suitable for modelling complex systems where information is imprecise or subjective. Fuzzy numbers enhance risk assessment by converting linguistic variables (*e.g.*, 'low,' 'medium,' 'high') into numerical intervals using membership functions. The main advantages of fuzzy logic include its ability to capture linguistic and qualitative information, simplify complex decision-making processes, and improve the accuracy of evaluations by taking uncertainties into account. By integrating fuzzy logic into methods including FMEA and AHP, decision-making under uncertainty becomes more reliable. In particular, in environmental risk assessment, fuzzy numbers help quantify uncertainties in evaluating the risks associated with engineered nanomaterials, improving the accuracy of risk prioritization and mitigation strategies (Topuz and van Gestel 2016). Susilawati *et al.* (2015) highlighted fuzzy logic's effectiveness in managing uncertainty in industrial processes, building on Zadeh's (1965) foundational work.

Integrating fuzzy logic with AHP and FMEA reduces uncertainty and refines RPN calculations, enhancing risk assessment accuracy. For instance, Abdelgawad and Fayek (2010) introduced a framework that uses fuzzification, inference rules, and defuzzification to enhance risk assessment. Fuzzy AHP complements this by aggregating criteria such as cost, time, and quality into a single priority metric, which has been shown to be effective in dynamic industries. This combined methodology has been applied also to improve supplier selection (Ramadhanti and Pulansari 2022), CNC router optimisation (Camci and Temur 2018), and wood decay management (Feili *et al.* 2018).

Building on this foundation, the fuzzy AHP-FMEA framework embeds fuzzy weights into FMEA criteria for more realistic RPNs (Grošelj and Dolinar 2023). Sensitivity analysis further strengthens these assessments by evaluating how parameter variations affect rankings, addressing uncertainties in high-variability industries (Wu *et al.* 2020; Więckowski and Sałabun 2024). Its success across industries, such as the assessment of submersible pump risk (Bhattacharjee *et al.* 2022), the robustness of the petrochemical ranking (Fatollah *et al.* 2022), and tailored risk prioritisation in wood manufacturing, highlights its versatility and value in supporting sustainability goals (Senthilkannan and Parameshwaran 2019).

By integrating fuzzy logic, AHP, and sensitivity analysis, the fuzzy AHP-FMEA framework provides reliable, nuanced risk assessments, making it indispensable for industries balancing quantitative data with expert insights.

EXPERIMENTAL

Materials

This study examined a mid-sized company operating in Croatia's wood-processing sector, specializing in the supply and processing of panel materials and hardware for furniture production and interior design. The company plays a vital role in the industry by offering a diverse selection of materials, including chipboards, MDF boards, veneer panels, and high-quality flooring solutions. It also provides specialized processing services such as custom cutting, edging, and CNC machining, catering to furniture manufacturers, interior designers, and construction firms. With multiple regional distribution centers and a technologically advanced production facility, the company ensures efficient material supply and processing capabilities. Its integrated approach, encompassing both raw material distribution and high-precision machining, supports the evolving needs of the wood-processing and furniture manufacturing industries. Additionally, its collaborations with leading global suppliers strengthen its position as a key provider of materials and technical solutions in the region.

Failure Mode and Effects Analysis (FMEA)

Failure Mode and Effects Analysis (FMEA) is a structured method for identifying potential failures in a product or process, assessing their impact, and implementing preventive actions. Developed by the U.S. military in the 1940s, FMEA has become a standard tool across industries to enhance safety and reliability. Its flexibility has led to widespread adoption in manufacturing, healthcare, and software development, supporting proactive risk mitigation and improving operational efficiency (Parsana *et al.* 2014; Kushwaha *et al.* 2020; Klarić *et al.* 2025).

The FMEA process involves a team that systematically analyses each component for potential failure modes, evaluates their effects on the system, and estimates the severity, occurrence, and detection likelihood of each. Traditional FMEA produces RPNs by multiplying three risk factor ratings, each assessed on a scale of 1 to 10 (Kushwaha *et al.* 2020; Table 1), with higher RPN values indicating riskier PFMs:

$$RPN_i = S_i \cdot O_i \cdot D_i, i = 1, \ldots, n. \tag{1}$$

For PFM i, (i=1,…,n), S_i represents the severity rating, indicating the strength of the impact of a PFM on production results. Higher severity levels correspond to PFMs that are more likely to cause significant disruptions to the production process. O_i denotes the PFM i occurrence score, reflecting its frequency of occurrence. D_i is the detection rating, measuring the likelihood of identifying the PFM i before it affects the production process. Higher detection scores signify PFMs that are harder to detect. The RPN facilitates risk prioritisation, enabling targeted interventions such as redesigns or enhanced testing.

However, the traditional RPN calculation method has several drawbacks (Sankar and Prahbu 2001; Liu *et al.* 2011; Li and Chen 2019), including:

- Issues with the RPN Formula: The formula to calculate RPN lacks justification for multiplying S, O, D. The resulting distribution (1 to 1000) is noncontinuous, with gaps, a heavy skew toward the lower end, and differences between values that lack meaning. Additionally, different combinations of S, O, D can produce identical RPNs, obscuring distinct risk effects. To address this, the fuzzy AHP-FMEA model uses a weighted arithmetic mean.
- Equal Weighting of Risk Factors: Traditional RPN assumes equal importance for S, O, D, which may not hold true. Although some studies consider their relative importance, they often assume uniform weighting across all PFMs (Hu *et al.* 2009; Wang *et al.* 2021), which is also not necessarily accurate. The fuzzy AHP-FMEA model assigns different weights to S, O, D for each PFM.
- Scale Limitations: The 1-to-10 scale makes it difficult to accurately evaluate PFMs for risk factors. The fuzzy AHP-FMEA model overcomes this by using a linguistic scale, which aligns better with human reasoning and simplifies the evaluation process.

Fuzzy AHP-FMEA Model

The Fuzzy AHP-FMEA model consists of four steps (Fig. 1). In the present work, Step 1 involved a structured expert evaluation to define process steps and identify potential failure modes (PFMs). A group of experts, including managers, engineers, and executives familiar with the company's work processes, participated in a series of workshops. Through process flow analysis and group discussions, the experts identified six key process steps representing critical stages in production. Subsequently, they defined 17 PFMs based on historical performance data, expert experience, and risk assessment brainstorming. Each PFM was then evaluated using the FMEA criteria—severity (S), occurrence (O), and detection (D)—forming the foundation for further analysis in the Fuzzy AHP-FMEA framework.

In Step 2, the identified PFMs were evaluated concerning the three risk factors S, O, D using a linguistic scale (Table 1). These assessments were then converted into triangular fuzzy numbers $\tilde{S}_i, \tilde{O}_i, \tilde{D}_i, i = 1, \ldots, n$. Three experts from Step 1 collaboratively evaluated the 17 PFMs based on these factors.

Step 3 involves evaluating the importance of risk factors for each PFM, identified in Step 1, and deriving their weights. A group of five external experts—managers and engineers with experience in wood-based manufacturing—was selected to compare the risk factors S, O, D for each PFM using a fuzzy linguistic AHP scale (Table 2). This process yielded fuzzy weights for the risk factors, denoted as $\tilde{w}_{S_i}, \tilde{w}_{O_i}, \tilde{w}_{D_i}, i = 1, \ldots, n$.

In Step 4 scores were aggregated for PFMs from Step 2 and the weights of S, O, D from Step 3 using the weighted arithmetic mean to obtain final fuzzy weights of PFMs.

$$\tilde{w}_i = \tilde{w}_{S_i}\tilde{S}_i + \tilde{w}_{O_i}\tilde{O}_i + \tilde{w}_{D_i}\tilde{D}_i, i = 1, \ldots, n. \tag{2}$$

Finally, Eq. 5 was used to defuzzify the weights. All calculations were performed in Excel.

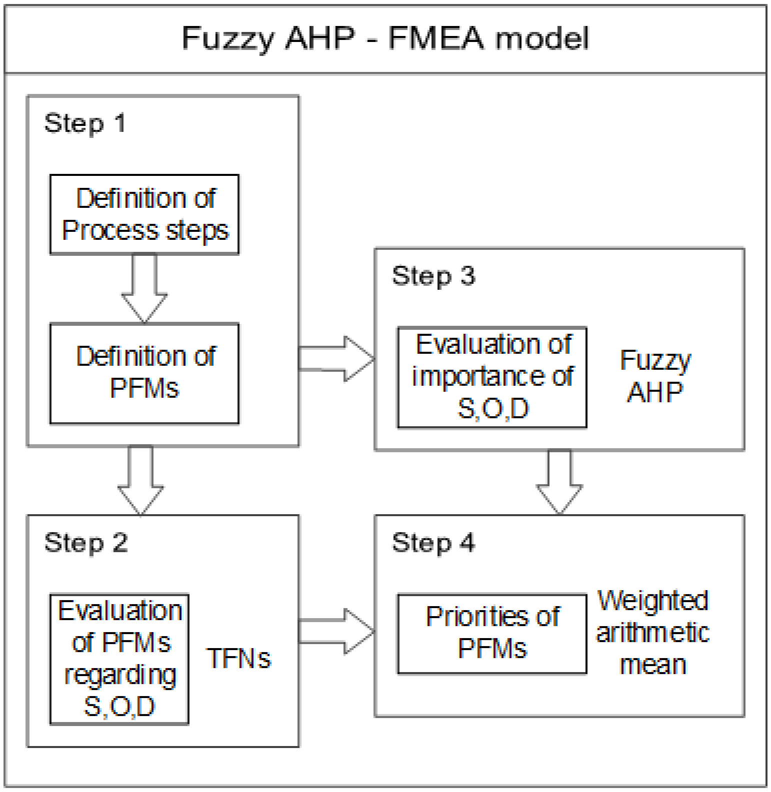

Fig. 1. Flowchart of the Fuzzy AHP-FMEA model

Table 1. Exact Value Scale, Linguistic Scale and TFNs for the Evaluation of PFMs Concerning Severity, Occurrence and Detection

Exact Values	Severity	Occurrence	Detection	TFNs
1	None	Nearly impossible	Almost certain	(1,1,2)
2	Very minor	Remote	Very high	(1,2,3)
3	Minor	Low	High	(2,3,4)
4	Low	Relatively low	Moderate high	(3,4,5)
5	Moderate	Moderate	Moderate	(4,5,6)
6	Significant	Moderately high	Low	(5,6,7)
7	Major	High	Very Low	(6,7,8)
8	Extreme	Repeated failures	Remote	(7,8,9)
9	Hazardous	Very high	Very remote	(8,9,10)
10	Very hazardous	Almost certain	Almost impossible	(9,10,10)

Fuzzy Analytic Hierarchy Process (AHP)

The fuzzy sets introduced by Zadeh (1965) were designed to better adapt the evaluation of objects to the human thought process and intuition. In MCDM methods, triangular fuzzy numbers (TFNs) can substitute exact values to handle uncertainty and vagueness more effectively during the evaluation process. The TFN is defined as a triplet (l, m, u), where m represents the most probable value, l is the minimum possible value, and u is the maximum possible value. Its membership function is described by an Eq. 3 and presented in Fig. 2.

$$\mu(x) = \begin{cases} \frac{x-l}{m-l}, & l \le x \le m \\ \frac{u-x}{u-m}, & m < x \le u \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

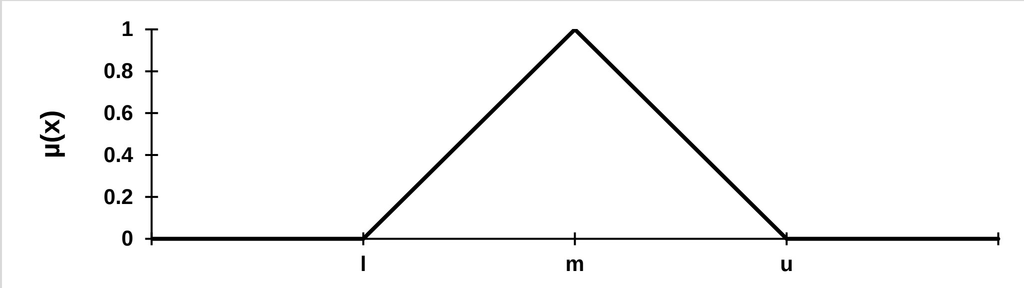

Fig. 2. Membership function of TFN

The simplified fuzzy arithmetic operations for TFNs are outlined below. Let $\tilde{x}_1 = (l_1, m_1, u_1)$ and $\tilde{x}_2 = (l_2, m_2, u_2)$ represent two TFNs. Then:

$$\begin{aligned} &\tilde{x}_1 \oplus \tilde{x}_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \\ &\tilde{x}_1 \ominus \tilde{x}_2 = (l_1 - u_2, m_1 - m_2, u_1 - l_2) \\ &\tilde{x}_1 \otimes \tilde{x}_2 = (l_1 l_2, m_1 m_2, u_1 u_2) \\ &\tilde{x}_1 \oslash \tilde{x}_2 = \left(\frac{l_1}{u_2}, \frac{m_1}{m_2}, \frac{u_1}{l_2}\right) \end{aligned} \tag{4}$$

To obtain the precise value for TFN $\tilde{x} = (l, m, u)$, the defuzzification process was applied using Eq. 5.

$$x = \frac{l+4m+u}{6} \tag{5}$$

TFNs provide a means to account for uncertainties in expert assessments in AHP.

AHP is a well-known MCDM method (Saaty 1980) that determines the priorities of objects by pairwise comparisons. In fuzzy AHP, expert judgments (*k=1,…, s)* are expressed using a linguistic scale.

Table 2. Saaty's Scale, Linguistic Scale and Corresponding TFNs of the AHP Method (Pitchipoo *et al.* 2013)

Saaty's Scale	Linguistic Preferences	Corresponding Fuzzy Preference
1	Equally preferred	(1,1,1)
2	Equally to moderately preferred	(1,2,3)
3	Moderately preferred	(2,3,4)
4	Moderately to strongly preferred	(3,4,5)
5	Strongly preferred	(4,5,6)
6	Strongly to very strongly preferred	(5,6,7)
7	Very strongly preferred	(6,7,8)
8	Very strongly to extremely preferred	(7,8,9)
9	Extremely preferred	(9,9,9)

The corresponding TFNs (Table 2) are collected in the following fuzzy pairwise comparison matrices:

$$\tilde{A}^{(k)} = \left(\tilde{a}_{ij}^{(k)}\right)_{nxn} = \left(l_{ij}^{(k)}, m_{ij}^{(k)}, u_{ij}^{(k)}\right)_{nxn}.$$

The reciprocal values $\tilde{a}_{ji}^{(k)} = \frac{1}{\tilde{a}_{ij}^{(k)}} = \left(\frac{1}{u_{ij}^{(k)}}, \frac{1}{m_{ij}^{(k)}}, \frac{1}{l_{ij}^{(k)}}\right)$ were used for reciprocal pairwise comparisons.

To derive the priorities from the fuzzy pairwise comparison matrix $\tilde{A}$, geometric mean (Buckley 1985) can be applied as follows.

$$\tilde{v}_i = (\tilde{a}_{i1} \otimes \tilde{a}_{i2} \otimes \cdots \otimes \tilde{a}_{in})^{\frac{1}{n}}$$
$$\tilde{w}_i = \frac{\tilde{v}_i}{\sum_{i=1}^{n} \tilde{v}_i}, i = 1, \ldots, n \tag{6}$$

and Eq. 5 can be used to defuzzify the fuzzy weights. The consistency of fuzzy pairwise comparison matrix $\tilde{A}$ should be determined by the consistency ratio CR of precise matrix of middle values $M = \left(m_{ij}\right)_{nxn}$ (Milošević *et al.* 2020):

$$\text{CR}=\frac{CI}{RI}, \text{CI}=\frac{(\lambda_{max}-n)}{(n-1)} \tag{7}$$

Using Eq. 7, CR is calculated from the consistency index (*CI)*, derived from the maximum eigenvalue λ_{max} and the random index (*RI)*. The fuzzy pairwise comparison matrix $\tilde{A}$ is considered acceptably consistent if CR<0.1.

To aggregate individual fuzzy pairwise comparison matrices into group fuzzy pairwise comparison matrix $\tilde{A}^{group}$, a max-min method is used (Kuo *et al.* 2002):

$$\tilde{A}^{group} = \left(\tilde{a}_{ij}^{group}\right)_{nxn}; \ \tilde{a}_{ij}^{group} = \left(l_{ij}^{g}, m_{ij}^{g}, u_{ij}^{g}\right)$$
$$l_{ij}^{g} = \min_{k=1,\ldots,s} l_{ij}^{(k)}, m_{ij}^{g} = \left(\prod_{k=1}^{s} m_{ij}^{(k)}\right)^{\frac{1}{s}}, u_{ij}^{g} = \max_{k=1,\ldots,s} u_{ij}^{(k)} \tag{8}$$

Integration of the Pareto Principle

The Pareto Principle, often referred to as the 80/20 rule, was incorporated into the prioritization process to focus on the most significant failure modes driving the majority of risks. This targeted approach ensures that corrective actions address high-impact areas, enabling effective risk mitigation. Guided by the principle, the analysis concentrated on the top-scoring PFMs within each process step, ensuring that efforts were directed toward the most critical risks.

Similar to the methodology of Keskin Çıtıroğlu *et al.* (2022), the Pareto Principle was applied alongside FMEA to systematically identify and rank the most significant risks, emphasizing areas requiring immediate attention. When combined with the fuzzy AHP-FMEA methodology, this approach created a robust framework for identifying and prioritizing critical risks, optimizing resource allocation, and achieving comprehensive risk mitigation.

RESULTS AND DISCUSSION

This section presents the outcomes of the fuzzy AHP-FMEA analysis. The results identified six key process steps and 17 PFMs (labelled D1 to D17) impacting wood manufacturing processes. These PFMs and their potential effects on production efficiency, customer satisfaction, and operational costs are summarised in Table 3.

Table 3. Process Steps, PFMs, and Potential Effects of Failure

Process Step	PMFs	Potential Effects of Failure
Employee education (EE)	D1 – Lack of knowledge of information system	Data loss, errors in product design or manufacturing process
	D2 – Insufficient CNC operators	Delayed delivery, increased costs, reduced customer satisfaction
	D3 – Delays in technical preparation	Delayed production and delivery, increased costs, reduced customer satisfaction
Occupational safety (OS)	D4 – Workplace injuries affecting productivity	Injuries to employees reduced productivity. Legal and financial liabilities, negative impact on company image
Distribution and logistics (DL)	D5 – Incorrect marking of completed orders	Incorrect shipment Customer complaints, increased costs
	D6 – Delayed deliveries and damaged products	Customer complaints, increased costs
Production planning and execution (PPE)	D7 – Incorrect order processing upon receipt	Delay in delivery
	D8 – Delay in sending work orders to production	Delay in production and delivery
	D9 – Insufficient workforce for task execution	Delay in production and delivery
	D10 – Improper packaging of semi-final products	Customer complaints, increased costs, damaged product during transport
	D11 – Equipment failure causing downtime	Delays in production, increased costs
Supply chain management (SCM)	D12 – Shortage of edge strips	Delays in production missed deadlines, and unhappy customers
	D13 – Production delays and missed deadlines	Delayed order fulfilment and unhappy customers
	D14 – Delayed customer deliveries	Delayed order fulfilment and unhappy customers
	D15 – Incorrect material delivery to the production site	Material sub9stitution during loading
	D16– Errors in material receipt and storage	Wrong materials, product defects, increased costs, delayed production, lower customer satisfaction
Internal communication (IC)	D17 – Material damage and delayed deliveries	Delayed delivery, increased costs, reduced customer satisfaction

Based on these findings, Table 4 compares the rankings derived from the Fuzzy AHP-FMEA model, traditional RPN, and the Fuzzy method with average S, O, D weights, highlighting critical differences in prioritisation. For example, D13 (production delays and missed deadlines) and D14 (delayed customer deliveries), ranked equally (3rd) in the traditional RPN, were elevated to second and third places, respectively, in the fuzzy model due to their significant impact on production schedules and customer satisfaction. In contrast, D17 (material damage and delayed deliveries), ranked 6th in traditional RPN, was deprioritized to 12th in the fuzzy framework, reflecting its more localised impact compared to other PFMs.

Table 4. Comparison of Fuzzy AHP-FMEA, Traditional RPN, and Fuzzy WAM Rankings

	Fuzzy AHP-FMEA	Rank	Traditional RPN	Rank	Average S, O, D Weights	Rank
D1	6.07	14	144	10	6.04	14
D2	5.26	16	160	9	7.16	13
D3	7.60	10	45	17	7.26	11
D4	7.86	8	54	16	7.17	12
D5	4.97	17	75	14	4.93	17
D6	8.68	4	378	3	8.55	3
D7	9.36	1	420	1	9.11	1
D8	8.10	6	180	8	7.84	6
D9	7.89	7	135	13	7.64	7
D10	7.66	9	224	7	7.47	10
D11	8.18	5	63	15	7.58	9
D12	6.22	13	144	10	5.96	15
D13	8.84	2	378	3	8.55	3
D14	8.81	3	378	3	8.59	2
D15	5.58	15	140	12	5.56	16
D16	7.58	11	392	2	7.59	8
D17	6.70	12	324	6	8.39	5

The analysis identified D7 (incorrect order processing upon receipt) as the most critical PFM (9.36), highlighting its potential to disrupt workflows and delay delivery schedules. Similarly, D6 (delayed deliveries and damaged products) (8.68) underscored the importance of logistics in maintaining material quality, while D11 (equipment failure causing downtime) (8.18) revealed vulnerabilities in machinery-dependent operations.

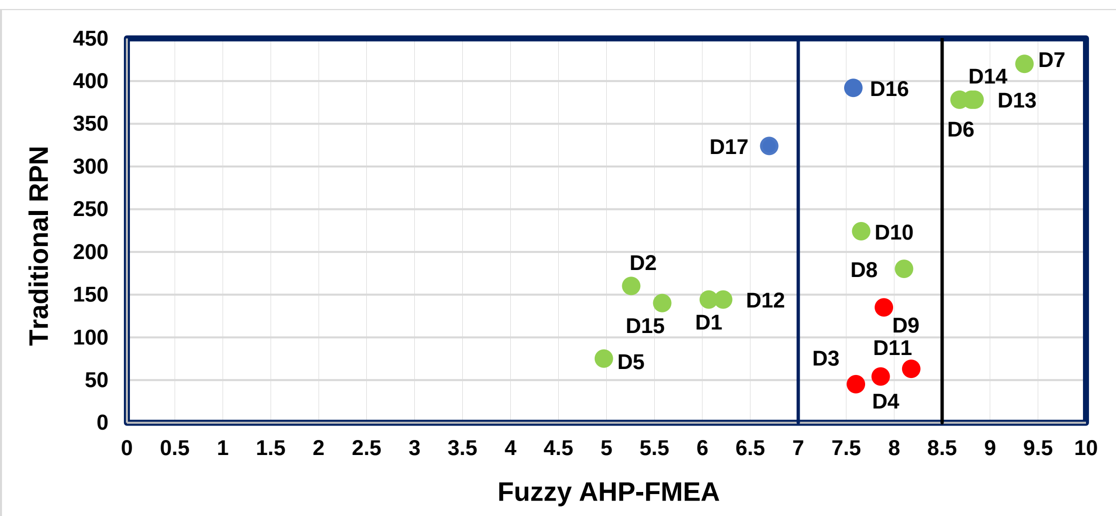

Fig. 3. Comparison between traditional RPN and Fuzzy AHP-FMEA

At the lower end of the spectrum, PFMs such as D5 (incorrect marking of completed orders) (4.97) and D2 (insufficient CNC operators) (5.26) exhibited more localised impacts and were deprioritized in the fuzzy model compared to risks affecting the entire production chain. The fuzzy AHP-FMEA framework refined risk prioritisation by aligning the identified risks with the operational needs of the wood manufacturing sector.

To better assess the advantages of fuzzy AHP-FMEA approach compared to traditional RPN and to highlight critical distinctions in prioritisation, Fig. 3 provides a graphical representation of the comparison between the results of two methodologies, categorising PFMs into three importance levels: very important (values above 8.5), medium importance (7.0 to 8.5), and low importance (below 7.0).

Some alignment was observed between the two methodologies (green dots). For example, D7 (incorrect order processing upon receipt) was ranked as the most critical PFM (Rank 1) in both models, reflecting consistency in recognising its significant impact on production workflows and delivery schedules. However, discrepancies were noted: red dots represent PFMs, such as D17 (material damage and delayed deliveries), which were identified as medium risk in the fuzzy model but were assigned lower rankings by the traditional RPN. Conversely, blue dots represent PFMs, such as D4 (workplace injuries affecting productivity), that were assigned higher rankings in the traditional RPN despite their lower operational impact in the fuzzy model.

Expanding on the observations of Fig. 3, Fig. 4 examines the influence of weighting methodologies in the fuzzy AHP-FMEA framework. It compares rankings obtained using specific weights for S, O, D with those calculated using average weights. This analysis highlights how tailored weight assignments can significantly impact PFM prioritisation. The average weights applied for the comparison were 0.445, 0.663, and 0.972 for S; 0.089, 0.149, and 0.261 for O; and 0.110, 0.188, and 0.327 for D.

The results showed that PFMs such as D17 (material damage and delayed deliveries) and D2 (insufficient CNC operators) received significantly higher rankings when specific weights were applied, reflecting notable differences between their individual weights and the averages. Conversely, PFMs with less variability in their individual weights, such as D7 (incorrect order processing) and D13 (production delays and missed deadlines), retained similar rankings under both approaches, demonstrating consistency in prioritisation.

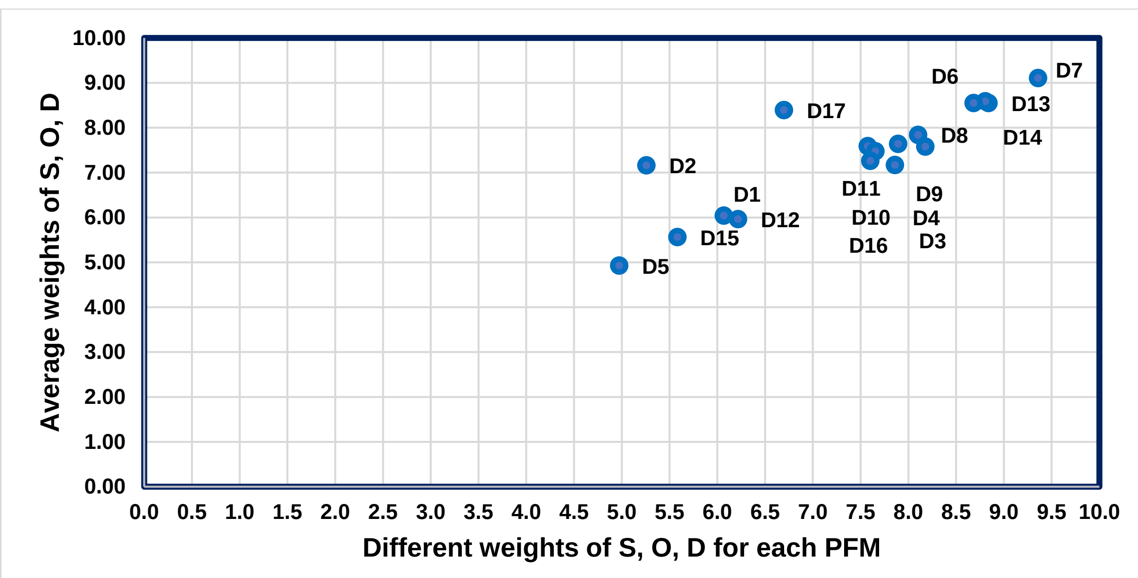

Fig. 4. Comparison between Fuzzy AHP-FMEA considering different weights of S, O, D and average weights of S, O, D

Figure 5 illustrates how PFMs were distributed across process steps and identified their criticality. Applying the Pareto principle, the analysis pinpointed the top 20% of the factors with the highest scores in each category, which accounted for a significant portion of the associated risks within each step of the process, as indicated by the red line.

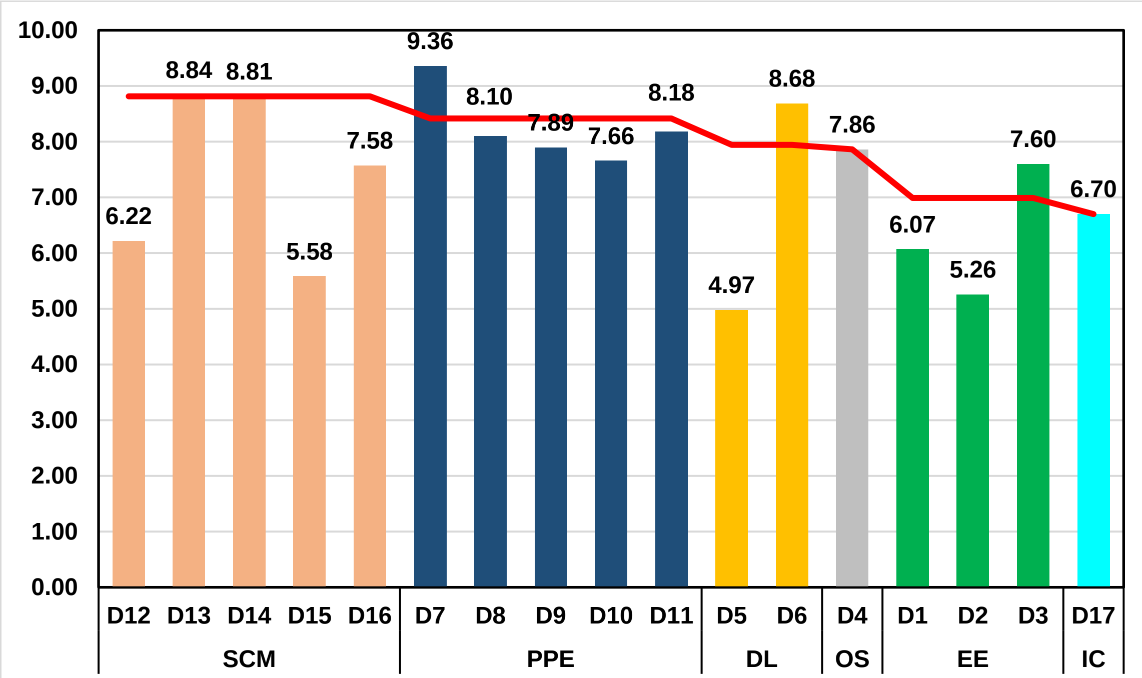

Fig. 5. PFMs united by Process steps

In the context of wood-based manufacturing, the analysis revealed the most critical PFMs within each category, which posed significant risks to production efficiency, product quality, and enhanced productivity:

- SCM: D13 (production delays and missed deadlines) and D14 (delayed customer deliveries) were identified as critical due to their potential to disrupt schedules, delay timelines, and harm customer satisfaction, ultimately leading to financial losses.
- PPE: D7 (incorrect order processing) emerged as a major risk, as errors in order management propagated through subsequent production stages, causing inefficiencies in cutting, assembly, and finishing operations.
- DL: D6 (delayed deliveries and damaged products) presented serious challenges, particularly due to its impact on material waste, transportation costs, and customer trust.
- EE: D3 (delays in technical preparation) impacted design accuracy and production timelines
- OS: D4 (workplace injuries affecting productivity) highlighted the importance of safety training.
- IC: D17 (material damage and delayed deliveries) underscored the need for improved material handling protocols and enhanced interdepartmental communication to prevent delays and ensure seamless workflows.
- SCM category has the highest value of the 80th percentile, indicated by the highest value of the red line.

Table 5. Proposed Corrective and Preventive Measures for PFMs

Process Step	PFM	Proposed Measures	Measure Type
EE	D1	Provide constant education to existing and new employees. Improve the documentation of the information system.	Preventive
	D2	Train employees to operate multiple machines, including CNC training. Increase the number of CNC operators.	Preventive
	D3	Offer technical drawing (CAD/CAM and Corpus) to improve product design accuracy and reduce manufacturing process errors. Utilise automated software for technical preparation.	Corrective
OS	D4	Conduct training on safe work practices and the proper use of protective equipment. Perform regular equipment inspections and maintenance. Implement comprehensive safety protocols and procedures. Conduct regular safety audits and risk assessments.	Preventive
DL	D5	Use appropriate documentation to mark load orders, with training in proper documentation procedures.	Preventive
	D6	Define delivery conditions and ensure timely communication with customers. Establish proper loading and unloading procedures and backup plans for delivery delays.	Corrective
PPE	D7	Accept orders only by e-mail or in person. Update and clarify ordering procedures; provide regular employee training.	Corrective
	D8	Adhere to the order of production scheduling and monitor capacity daily. Adjust production orders to align with production sequences.	Preventive
	D9	Plan workplace schedules, coordinating production plans with job distribution. Review and update workforce allocation procedures regularly.	Preventive
	D10	Address inadequate pallet packaging by using appropriate materials, tools, and production parameters. Maintain machines and suction systems; provide employee training on proper packaging techniques.	Preventive
	D11	Use quality materials and appropriate production parameters with regular maintenance of equipment and tools. Develop backup plans to mitigate equipment failure.	Preventive
SCM	D12	Expand the supplier market for edge bands to cover all décor. Implement periodic audits and quality checks.	Preventive
	D13	Confirm and verify orders with project and procurement managers. Enhance communication and coordination with suppliers.	Corrective
	D14	Organise and maintain timely communication with transport companies. Establish multiple transport options and alternatives.	Corrective
	D15	Scan barcodes on loading orders and enforce relevant procedures. Create and implement a standardised loading checklist.	Preventive
	D16	Organise pallets according to dimensions. Inspect and verify the incoming materials. Ensure adequate labelling and tracking of materials. Conduct regular inventory audits and reconciliations.	Preventive
IC	D17	Update and implement procedures for internal communication. Provide consistent education and define responsibilities clearly. Ensure timely reporting of issues. Conduct regular communication meetings and feedback sessions.	Corrective

These findings highlighted the importance of addressing high-risk PFMs to reduce risks and optimise operations in the wood-based manufacturing sector. To tackle these challenges, Table 5 outlines tailored corrective and preventive measures designed to address critical risks and drive significant process improvements across the company's key operations. Based on the fuzzy AHP-FMEA analysis, the recommendations prioritise targeted corrective actions for high-priority PFMs while emphasizing preventive measures to support long-term resilience.

The corrective measures focus on rectifying inefficiencies in PFMs such as D3 (delays in technical preparation), D4 (workplace injuries affecting productivity), D6 (delayed deliveries and damaged products), D7 (incorrect order processing), D13 (production delays and missed deadlines), D14 (delayed customer deliveries), and D17 (material damage and delayed deliveries). Proposed actions include improving technical preparation with automated tools, enhancing material handling procedures, defining delivery protocols, clarifying order processing systems, and optimising supplier coordination to meet deadlines.

Conversely, preventive measures aim to mitigate risks and foster long-term resilience by addressing PFMs such as D1 (lack of knowledge of the information system), D5 (incorrect marking of completed orders), D8 (delays in sending work orders to production), D10 (improper packaging of semi-finished products), D11 (equipment failure causing downtime), D12 (shortage of edge strips), and D16 (errors in material receipt and storage). Strategies include comprehensive employee training, adherence to safety and operational protocols, consistent monitoring of production and logistics, and proactive equipment maintenance to minimise disruptions and ensure stability.

This structured approach provides a robust response to operational risks. Corrective measures address urgent issues like delays, order inaccuracies, and material damage, while preventive strategies build a foundation for sustainable growth through enhanced education, safety, and operational efficiency.

Discussion

The proposed framework bridges the gap between traditional RPN methods and more sophisticated ranking techniques. Unlike conventional models that often prioritise computational complexity over interpretability, the fuzzy AHP-FMEA approach balances methodological rigour with practical applicability. Furthermore, it assigns tailored weights and incorporates linguistic scales, improving the robustness of the prioritisation process. This advancement aligns with findings from Liu *et al.* (2015) and Fattahi *et al.* (2020), who emphasised the value of integrating fuzzy logic to address subjectivity in complex industrial settings. Similarly, Abdelgawad and Fayek (2010) demonstrated the application of fuzzy FMEA and AHP in construction, highlighting how these methodologies address variability and uncertainty, challenges that are critical in both the construction and wood manufacturing industries.

The framework presented here offers unique strengths in its adaptability to the complexities of wood manufacturing processes. Furthermore, unlike other approaches such as Li *et al.* (2021), which emphasised normalization algorithms for floating offshore wind turbines, this study focusses on the integration of expert-driven weighting processes. While normalisation techniques could further enhance ranking precision, the reliance on expert input ensures that operational nuances are well captured, which is essential in industries with variable production processes such as wood manufacturing.

Furthermore, expert judgment played a crucial role in improving the reliability of this study's framework. Using the expertise of managers and engineers with deep knowledge of the wood manufacturing process, the model ensured contextually relevant weighting of severity, occurrence, and detection factors. This integration of expert insights not only improved the precision of risk assessments but also aligned priority outcomes with operational realities.

The findings also underscored the criticality of addressing high-priority failure modes, particularly "incorrect order processing" (D7), "production delays and missed deadlines" (D13), and "delayed customer deliveries" (D14). These risks were identified as the most impactful, consistent with observations from similar studies (Camci and Temur 2018; Urbina *et al.* 2022). Addressing these risks is essential to improve production efficiency, maintain product quality, and ensure customer satisfaction.

Furthermore, the sensitivity analysis revealed the robustness of the fuzzy AHP-FMEA methodology. Even when the weights for the risk factors varied, the prioritisation of critical failure modes remained consistent, strengthening the reliability of the approach. For example, "incorrect-order processing" (D7) consistently emerged as the top priority across all weighting scenarios, underscoring its potential to disrupt workflows and delay delivery schedules.

The tailored corrective measures proposed in this study specifically address critical PFMs such as D3, D4, D6, D7, D13, D14, and D17 aligning with industry needs for operational precision and customer responsiveness. For instance, improving order accuracy (D7) through updated ordering protocols and training reduces propagation of errors across production stages, while enhancing communication protocols (D14) mitigates delivery delays and fosters stronger supplier and customer relationships. These targeted actions not only resolve immediate bottlenecks but also build resilience against future disruptions.

Finally, further refinements, such as normalisation and weighting adjustments explored in other studies, could complement this robustness by offering additional resolution for mid-range risks. However, the stability of prioritisation results in this framework underscores its practical value even without these enhancements.

Practical Implications

The study provides actionable insights for practitioners, including:

- Enhancing employee training programmes, such as CNC education and technical drawing skills, consistent with Susilawati (2021).
- Strengthening internal communication protocols to address inter-departmental delays, as emphasised by Zahra *et al.* (2024).
- Improving supply chain management to mitigate risks associated with "production delays and missed deadlines" (D13) and "delayed customer deliveries" (D14), echoing recommendations from Boran and Gökler (2019).

The findings from Table 5 further underscore the interconnected nature of risks in wood manufacturing. Addressing D13 and D14 through improved supply chain management highlights the critical role of logistics and material handling in ensuring timely production and delivery. These insights resonate with studies in related fields, such as Zahra *et al.* (2024), which advocate for enhanced interdepartmental coordination to mitigate similar risks in high-variability production environments.

These corrective measures are tailored to the operational context of wood manufacturing, making the fuzzy AHP-FMEA framework particularly effective for addressing variability in production, logistics, and material handling. Although advanced monitoring tools, as demonstrated in other studies, could augment these interventions, the proposed framework already offers substantial practical benefits.

Limitations and Future Directions

While this study demonstrated the adaptability and utility of the fuzzy AHP-FMEA framework, it was conducted within a single wood-based manufacturing company, which may limit its generalisability. Expanding its application to multiple companies or industries, as demonstrated by Fatollah *et al.* (2022) in the petrochemical sector, could validate its broader utility and uncover additional sector-specific insights.

Furthermore, integrating economic dimensions, such as cost and profit considerations, could enhance the framework's practical relevance, as suggested by Fattahi *et al.* (2020). Future research could also explore integrating advanced automation technologies, such as machine learning, to refine weighting calculations and further mitigate subjectivity.

By addressing both the technical and operational aspects of risk management, the fuzzy AHP-FMEA framework supports informed decision making and promotes continuous improvement. Its adaptability to dynamic and complex industrial settings makes it a valuable tool for risk prioritisation and operational enhancement. While this framework provides a robust methodology for wood manufacturing, integrating select refinements such as normalisation algorithms or predictive technologies could further enhance its precision and applicability.

CONCLUSIONS

1. The fuzzy analytic hierarchy process-failure mode and effects analysis (AHP-FMEA) framework effectively refines traditional risk priority number (RPN)-based risk assessments by incorporating tailored weighting and linguistic evaluations, resulting in improved prioritisation of failure modes in wood-based manufacturing processes.
2. Critical potential failure modes (PFMs), such as “incorrect order processing” (D7), “production delays and missed deadlines” (D13), and “delayed customer deliveries” (D14), were identified as high-priority risks. Addressing these risks is crucial for optimising production efficiency, maintaining product quality, and enhancing customer satisfaction.
3. Integration of fuzzy logic with FMEA mitigates limitations related to subjective assessments, inconsistent factor weighting, and scale redundancy. This approach offers a more nuanced and accurate assessment of risk priorities compared to traditional FMEA methods.
4. The findings of this study emphasised the importance of employee training, internal communication, and workflow optimisation as key corrective measures to address high-risk PFMs, aligning with broader objectives of operational improvement and sustainability in the manufacturing sector.
5. Applying the Pareto principle revealed that the top 20% of PFMs accounted for approximately 80% of the associated risks, underscoring the value of focussing resources on the most impactful issues to achieve efficient risk mitigation.

6. The study contributes to the literature on risk management in manufacturing by demonstrating the applicability and benefits of combining fuzzy AHP and FMEA methodologies in a wood-based manufacturing context, providing a model that could be adapted to other industries.

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