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Efficient Fine Tuned Trapezoidal Fuzzy-Based Model for Failure Mode Effect Analysis Risk Prioritization

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ABSTRACT Many industries struggle with different project failures including Enterprise Resource Planning (ERP) implementations projects which has high failure rates too. Failure Mode Effect Analysis (FMEA) is an extensively utilized to analyze failure modes in risk assessment in various industry projects including ERP implementation projects. Nevertheless, in the traditional FMEA system, ignoring the Interdependencies among various failure modes as well as the relative importance of risk and non-injective and non-subjective nature of conventional RPN functions leads to challenges in analysing and assessing the risk. This may mislead in the addressing the prioritization of the Risk. Therefore, an efficient FMEA framework is proposed using Fine Tuned Trapezoidal Fuzzy-based Technique for Order of Preference by Similarity to Ideal Solution (FTTF-TOPSIS). The developed FMEA framework focuses to avoid data complications while preparing or collecting the data by using a hierarchical matrix management for data preparation. Uncertain risk, cost, and relative dependency are considered as additional parameters regarded by the work to calculate RPN. Mathematical models such as conservative method together with the Square Root Kragten Method (SRKM) are used to find the relative dependency along with uncertain risks. Thereafter, a highly reasonable along with credible outcome to rank the risk, FTTF-TOPSIS is employed. Finally, to demonstrate the proposed method's efficiency together with benefits, a comparation is made with the other models.

INDEX TERMS Conservative method, cost, enterprise resource planning, FMEA, FTTF-TOPSIS, risk assessment, RPN, square root Kragten method (SRKM), uncertain risk.

I. INTRODUCTION

From the literature it is evident that the project involves a lot of risks and various projects failed due to a number of reasons. We have known for decades that IT projects often fail. Research indicates ERP implementations have high failure rates too. ERP implementation is often considered as a difficult, expensive, and very risky process. ERP system gives diverse benefits to the company. ERP systems reduce the majority of the operational challenges like production schedules, decreasing inventory, lowering operational costs, maximizing productivity, offering control over materials, enhancing quality, etc. ERP as well aids to break down silos, enrich cooperation amongst diverse functions, which ultimately produces a greater quality of product and service, lessen time to market, enhances production with reduced cost, and lastly enhance market share with customer satisfaction.

Despite the benefits of ERP systems, several ERP systems were unsuccessful in producing outcomes. Mostly the failures are owing to ERP systems' poor implementation according to [1]. So, an appropriate Risk Management (RM) may help the project managers to reduce both the anticipated and unknown risks on a variety of projects. Failure to effectively manage risk can cause projects to go over budget, fall behind schedule, miss important performance targets, or show any combination of these issues. FMEA utilized in systems, designs, along with the product has greatly drawn interest [2], [3]. Not like other Risk Assessment (RA) tools, which look

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for remedies after the failure happened, FMEA's major role embrace identifying several potential failures and estimating their risk. Next, to lessen the possibility and severity of failure or prevent dangerous loses [4], [5]. To notify RM decisions, Aeronautical engineering proposed FMEA in the 1960s [1]. It is as well called FMECA (FM Effects and Criticality Analysis), while it is employed in a critical study [6], [7].

The FMEA technique has been broadly used in automotive, electronics, medical and health, aerospace, and other sectors [8], [9]. But different original RPN formula's deficiencies have also gained attention; for example, in RA, there is complexity in managing the intricate uncertainty [10]. In conventional FMEA, the RPN is utilized to rank the recognized FMs. Normally a FM's RPN value is acquired as the product of '3' Risk Factors (RFs), i.e., Occurrence (O), Detection (D), along with Severity (S) [11], [12]. The FMs with greater RPN values are assigned a superior priority for remedial measures in an FMEA process. Despite that the traditional FMEA is capable of coping with the risk management issues, its applicability is restricted due to several inadequacies as highlighted in earlier research [13], [14].

For instance, as a consequence of the ambiguity and uncertainty brought by lack of information and individual cognitive restrictions, it is complex for professionals to accept precise numbers to gauge RFs. Uncertainties can be showcased in several ways, like restricted professional knowledge together with experience, which may bring about erroneous and incomplete FMEA team members' evaluations [15], [16]. Diverse O, S, together with D's combinations can create a similar RPN value, even if the FMs' risk implications are unlike at the same level. The RFs' weights are assumed to be alike, which might be incompatible with real situations. Furthermore, the relative dependency between the risks is questionable and debatable [17], [18]. It is intricate for FMEA team members to analyze the risk and to discover a solution to lessen it, owing to the rising intricacy of RA issues. To overcome the prevailing problem, the paper has created an FMEA approach utilizing the FTTF-TOPSIS.

The main contribution of this paper are as follows:

a. An efficient FMEA framework is proposed using Fine Tuned Trapezoidal Fuzzy-based Technique for Order of Preference by Similarity to Ideal Solution (FTTF-TOPSIS).

b. To avoid data complications, a hierarchical matrix management data preparation is used.

c. Uncertain risk, cost, and relative dependency are considered as additional parameters regarded by the work to calculate RPN.

d. Mathematical models such as conservative method together with the Square Root Kragten Method (SRKM) are used to find the relative dependency along with uncertain risks.

e. A highly reasonable along with credible outcome to rank the risk, FTTF-TOPSIS is employed.

The paper's remaining part is arranged as: A survey of present alterations to FMEA in the literature is exhibited in Section II. The proposed technique is mentioned in Section III. A comparative analysis with other related techniques to authenticate the proposed technique is demonstrated in Section IV. Lastly, the conclusion is presented in Section 5.

II. LITERATURE SURVEY

Wang *et al.* [19] introduced a method that simultaneously encompassed decision makers' psychological behaviour and interface linkages amongst risk components. Initially, it evaluated the FMEA team member's mental behaviour during RA. To measure the risk variables' RA, the prospect theory was employed. Next, the Fuzzy Measure (FM) along with Choquet integral was utilized to amalgamate the FMs' potential value for every risk component. The entropy weighting methodology was employed to produce the overall RPN related to every FM and the relative preference relation was established to prioritize the FMs after it computed the prospect value for every FM. But the method didn't ponder the hidden risk implications.

Ghoushchi *et al.* [20] designed a 3-step approach to handle the FMEA's disadvantages. In the 1st phase, FMEA was employed to find FMs and provided values to the RPN. Next, the Fuzzy Best-Worst Method (FBWM) was wielded to compute these parameters' weights centered on expert judgments. For prioritizing the failures with Multi-Objective Optimization by Ratio Analysis centered on the Z-number theory (Z-MOORA), the previous phases' outcomes were used as a foundation, in the third phase. When analogized to other common methods like FMEA in conjunction with fuzzy MOORA, this methodology was employed in the automotive spare parts business; in addition, it revealed that failures were completely prioritized. The suggested method didn't regard the risk interdependencies across failure types.

Shiue *et al.* [21] developed an integrated RA model that merged several techniques to give an FMEA for inclusive FM rating. Initially, to ameliorate the assessment's comprehensiveness, the predicted expenses along with environmental security indicators were combined into the FMEA. Next, the RFs' significant network relationship map was produced with the Decision-Made Trial in conjunction with Evaluation Laboratory (DEMATEL) methodology, to detect the key elements. Lastly, the '4' incorporated MCDM methodologies along with the TOPSIS concept was wielded to rank the FMs. Also, for describing the suggested techniques' effectiveness together with robustness data as of a machine tool manufacturing companies' survey was utilized; however, the method didn't regard the comparative significance of risk variables.

Lo *et al.* [22] created a method that combined multiple-criteria decision-making with grey theory. The method had numerous benefits: adding the expected cost into the actual RPN to imitate the real resource restrictions, considering the diverse severities' weights, occurrence, detectability, together with cost centered on the FBWM in RPN computation, along with utilizing the grey interval literary variables to handle data ambiguity. Real data from a multinational electronics company were deployed to prove the methods' utility and efficiency. The approach gave a substitute risk priority solution for product development; however, it was unsuccessful to manage undefined risk.

Wang *et al.* [23] offered an FMEA methodology, the FM, and Shapley index that were utilized to design the interaction connections amongst Risk Indicators (RIs), in addition, to establish the weights of these indicators. To replicate the FMEA members' psychological behaviour, the comprehensive and widespread TODIM technique with FM and Shapley index was rendered. It was also employed to compute the risk priority of every FM. To signify improbability in the risk appraisal mechanism, Trapezoidal Fuzzy Numbers (TrFNs) were utilized. Also, to amalgamate FMEA members' RA data into a RA matrix that considered possible correlations amongst these members, a RA data amalgamation with TrFNs-WAIA operator centered on Shapley Choquet was created. This study did not consider cost whilst computing RPN.

Qin *et al.* [24] proffered a method that merged Interval Type-2 Fuzzy Sets (IT2FSs) with the Evidentiary Reasoning (ER) technique that was capable of conquering a few of the difficulties of the existent FMEA technique along with handling uncertainty more effectually. Initially, it gave an extra definite representation of the RFs in the IT2FSs along with enhanced the '3' RFs' relative weight. Next, the FMs in association with every RF were estimated with Belief Structures (BS). Lastly, the BSs were merged with the ER method with the '3' risk variables. For checking the technique's feasibility, an application for a steam valve system was designed, in addition, the outcomes exhibited the techniques' worth; however, the ranking method was intricate.

III. PROPOSED FMEA FRAMEWORK

To define, detect, and eliminate potential along with known risks, the FMEA is utilized. In the classic FMEA, the risk is quantified as an indicator by using the RPN in which the process of computation is effortless. However, owing to the existence of uncertain risks, inadequate scientific basis in RPN computation, the need for accurate risk determination, along with neglecting the RFs' weights, there exist numerous cons in the previous FMEA. Additionally, to execute RA along with RP, the factors chosen for RPN aren't efficient.

Therefore, developing a methodology that overcomes the limitations of the conventional FMEA becomes very vital. Additionally, three key risk variables such as Relative dependency, Uncertain risk, and cost are used to evaluate the capability of ranking FMs. So, a FMEA framework by utilizing the FTTF-TOPSIS is generated, which is exhibited in Fig 1.

A. PREPARATION

In the execution of FMEA, the ERP is studied at first. To decide on the impacts and causes of probable failures, the interaction between the ERP user, Costs, time, budgets, and its working environment must be fully understood. A potential FM is extended as a system, subsystem, or component, which possesses the ability to fail prior to getting its design objectives. The initial potential failure causes the secondary

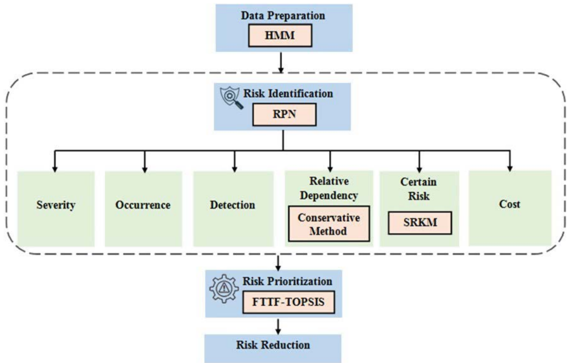

FIGURE 1. Proposed FMEA framework.

failure, that is to say, the failure of a lower-level component owing to the deficiency in spontaneous attention of the ERP implementation staff. The component and its function for every possible FM should be well documented. The presumption is that there may occur a failure; however, it doesn't have to. After the failure, the breakdown mode's consequence is proffered as the imminent failure effect; also, it should be centered on the evaluation of the system reaction. To process further, the data's preparation should be structured. Identifying the risk with lower computation time with precise detection along with handling the uncertain data are done with the collected data's aid, which is made into matrix management.

For instance, an ERP implementation, which is required for accessing the risk, is considered here. '6' stages of risk $\left(M_i^n = M_1^1, M_2^2, M_3^3, M_4^4, M_5^5, M_6^6\right)$ are included in this. Here, the number of processes to gather the data regarding the risk possibility is specified as n.The risk is completely understood under the provision of the ERP users (GL_i^H), Organizational/ management team (SP_i^H), Technical team (MT_i^H), Internal people team (TL_i^H), external people team (PM_i^H), Software manager (QM_i^H) to appraise the risk. Here, the data's hierarchical formation is signified as H. For effortless processing, the data is made under HMM as, (1), shown at the bottom of the next page, where, the data is constructed in a hierarchical manner as $\underbrace{d}_{d_1\ d_2\ d_3\ d_4}$ to classify the data provided by the team, where, the RFs, which might be operational, analytical, organizational, or technical, are specified as R_f, the data viewer is signified as I_G.

Regarding the data viewer, the risk's chances are classified to perform the hierarchical structure. For exemplar, the data amassed might bring about a complication if the risk is occurred owing to internal people who possess chances of ERP exploitation risks under different circumstances. As mentioned above, the hierarchical structure classifies them under every single categorization of risks to defeat the aforementioned issue.

B. RISK IDENTIFICATION

Risk identification observes the prepared data and prepares for the prioritization of risk. A direction to rank the potential failures; in addition, to recognize the suggested actions for outlines or process modifications, which would mitigate severity or occurrence, is provided by the RPN. The RPN Estimation is supported by the Risk Indexed Parameter (Γ, Θ and D). A higher risk of failure is indicated by a higher RPN. To lessen the risk, restorative methodologies have to be introduced.

However, an efficient RA with RP was not provided by simply computing occurrence, severity, together with detection. The constraints like the similar sort of identical values can be acquired for various data set points of Γ, Θ, along with D; nevertheless, the RA might be entirely varied. The risk's priority might be altered by the risk's relative dependence, uncertain risk, along with the dissimilarity of hazard descriptions amongst FMs. Additionally, uncertain risk value, relative dependency, and cost for RA are considered here.

$$RPN\,[\boldsymbol{P}] = \Gamma \times \Theta \times D \times \Re_D \times U_R \times C_s \tag{2}$$

(i) Severity (Γ)

The severity of the possible hazard's consequence is estimated by the seriousness rating. Whilst computing the scoreΓ,theFM's effectisconsidered.

(ii) Occurrence (Θ)

The likelihood of a prospective risk existing in a particular condition or context is computed by Occurrence. The impact's likelihood occurring as a consequence of a FM is analogized with the probability score.

(iii) Detection (D)

Detectability refers to the chance of detecting a failure before determining its impact on the technique or framework being examined. The D score is calculated based on the ability to recognise the breakdown mode's outcome.

(iv) Relative dependency ($\Re_D$)

While it is normal to identify and manage risks individually, certain project hazards are in fact interdependent. For example, a risk where, on the one hand, an ERP system contains inaccurate goals and objectives and, on the other hand, there is a poor ERP implementation strategy which has a dependence connection. The dependence connection in this situation is that if the chance of the first risk event rises, the likelihood of the second risk event also rises. In order to improve the RPN, the work has used a conservative method. A conservative methodology is utilized here to enhance the RPN. In this methodology, the implicit assumption is that it will place a superior priority on minimizing risks, which has a larger dependency effect; however, it places a lower priority on utilizing chances, which possess a lower dependency effect.

The conservative methodology prefers the largest value as of the direct predecessors' entire Risk Dependency Values or Risk Dependency Multipliers during the higher dependency influence on a risk's possibility. The project prioritizes risk reduction by providing higher priority or lower priority over opportunity exploitation, which is regarded as the implicit assumption. This model would augment the risk's dependency effect and it might require extra resources; thus, the project must be significant to the organization, or the risk must possess a vital effect on the project goals to utilize the aforementioned strategy for risks. Conversely, the dependency effect on an opportunity is mitigated by the strategy. There is an assumption that for managing opportunities, the project has only limited resources or the opportunities don't provide more values to the project purposes.

Let $\chi_x = f\,(\mathbf{P}_x, \mathbf{I}_x)$ along with $\mathbf{P}_x$ has k direct predecessors, say $\chi_1, \chi_2, \ldots.\chi_x$, where $x \neq 1\ldots.k$. The posterior risk $\chi_x^+ = f\left(\mathbf{P}_x^+, \mathbf{I}_x\right)$, wherein, $\mathbf{P}_x^+ = \mathbf{P}_x + \wp\ or\ \mathbf{P}_x^+ = \mathbf{P}_x - \lambda_x$. Posterior risk χ_{ab} between two risks χ_a and χ_b is formulated as,

$$\chi_b^{+a} = f\left(\boldsymbol{P}_b^{+a}, \boldsymbol{I}_a\right) = f\,(\boldsymbol{P}_b + \chi_{ab}, \boldsymbol{I}_b)\ where\ \boldsymbol{P}_b^{+a} = \boldsymbol{P} \tag{3}$$

In this, $\Re_D = \{\Re_{x1}, \Re_{x2}, \Re_{x3}, \ldots..\Re_{xn}\}$ specifies the Risk Dependency Values as:

$$\Re m_x = \{\Re m_{1x}, \Re m_{2x}, \Re m_{3x} \ldots..\Re m_{nx}\} \tag{4}$$

It signifies the set of Risk Dependency Multipliers. If there is a risk dependency multiplier $\Re m_{ab}$ betwixt'2' risks χ_a and χ_b, then the posterior risk is expressed as,

$$\chi_b^{+a} = f\,(\boldsymbol{P}_b \Re m_{ab}, \boldsymbol{I}_b)\ where\ \boldsymbol{P}_b \Re m_{ab} = \boldsymbol{P} \tag{5}$$

Lastly, the Relative risk dependency is achieved by selecting the maximum value as of the Risk Dependency Value and Risk Dependency Multipliers as follows,

$$\wp_x = Max\,(\Re_{x1}, \Re_{x2}, \Re_{x3}, \ldots..\Re_{xn}) \tag{6}$$

$$\lambda_x = Max\,(\Re m_{1x}, \Re m_{2x}, \Re m_{3x} \ldots..\Re m_{nx}) \tag{7}$$

(v) Uncertain Risk (U_R)

To produce more robust findings when compared to other people's viewpoints, it is vital to prioritise the failures in terms of the uncertainty in the RPN variables. The risk assessment is influenced by the unclear risk by modifying the risk priority. In order to accomplish an appropriate risk assessment of a project, the unknown risk should be considered. The work established the square root kragten method (SRKM), which simplifies the computation of combined uncertainty by utilising finite differences instead of derivatives. When compared to the Kragten approach, the created SRKM delivers a more in-depth intuitive estimate of uncertain risk. If the

$$\boldsymbol{P} = \begin{bmatrix} R_f/I_G & GL_i^H & SP_i^H & MT_i^H & \cdots & N_G^H \\ M_1^1 & d & d & d & \cdots & M_{n\times 1}^f \\ M_2^2 & d & d & d & \cdots & M_{n\times 2}^f \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ M_1^1 & GL_{1\times m}^N & SP_{2\times m}^N & MT_{3\times m}^N & MT_{4\times m}^N & N_{n\times m}^N\ n \end{bmatrix} \tag{1}$$

uncertainties in the inputs are inferior to the respective values of the input quantities, then the approximation is valid.

The measurands or riskχ that is computed as of the input quantities $\mathbf{P}_1, \mathbf{P}_2,$ *and* $\mathbf{P}_3$ along with the uncertainties $U_{P_1}, U_{P_2},$ *and* U_{P_3}intended for the input quantities are analyzed normally. From this, the measurands' computation is executed separately for every single input magnitude ($\chi\mathbf{P}_1, \chi\mathbf{P}_2,$ *and* $\chi\mathbf{P}_3$); thus, the corresponding values are appended to their uncertainties every time as,

$$\chi \boldsymbol{P}_1 = \frac{\left(P_1 + U_{P_1}\right)\boldsymbol{P}_2}{\boldsymbol{P}_3^2} \tag{8}$$

$$\chi \boldsymbol{P}_2 = \frac{\left(P_2 + U_{P_2}\right)\boldsymbol{P}_1}{\boldsymbol{P}_3^2} \tag{9}$$

$$\chi \boldsymbol{P}_3 = \frac{\boldsymbol{P}_1\boldsymbol{P}_2}{\left(\boldsymbol{P}_3 + \chi P_3\right)^2} \tag{10}$$

Owing to the inclusion of the uncertainty U_{P_1} to the value of its corresponding input quantity, the value of the measurands χ varies for $\chi\mathbf{P}_1$. Therefore, every single input source's uncertainty component in the unit of the measurands χ is proffered by the difference $|\chi\mathbf{P}_i - \chi|$, in accordance to,

$$U_\chi\left(\boldsymbol{P}_1\right) = \sqrt{|\chi\boldsymbol{P}_1 - \chi|} \tag{11}$$

$$U_\chi\left(\boldsymbol{P}_2\right) = \sqrt{|\chi\boldsymbol{P}_2 - \chi|} \tag{12}$$

$$U_\chi\left(\boldsymbol{P}_3\right) = \sqrt{|\chi\boldsymbol{P}_3 - \chi|} \tag{13}$$

Lastly, the amalgamated standard uncertainty of χ is estimated as,

$$U_\chi = \sqrt{\sum\nolimits_{i=1}^{N} U_\chi^2\left(\boldsymbol{P}_i\right)} \tag{14}$$

(vi) Cost (C_s)

The amalgamation of the opportunity of occurrence of risk along with the degree of that harm estimates the cost; unfortunately, no additional data is offered regarding how the possibility of occurrence along with severity is to be "combined". Specific failure's predicted cost is simply notated as,

$$\begin{aligned} C_s = &\Pr ob(\mathit{failure}) \times \Pr ob(\mathit{not\ an\ failure}) \\ &\times \cos t \ \mathit{of\ harm\ if\ it\ occurs} \end{aligned} \tag{15}$$

Lastly, the risk's score has been gauged regarding the RPN; after that, regarding the score, the ranking is conducted, (16), as shown at the bottom of the next page.

C. RISK PRIORITIZATION

The decision matrix is created regarding the strategy being selected; then, it is ranked by wielding the FTTF-TOPSIS methodology. The prevailing ranking methodologies bring about a poor ranking of the risk priority owing to their exposure to numerous attributes-centric decisions making along with uncertain alterations in the strategies and outliers. To conquer the aforementioned complications along with to get an effectual ranking model, the Z-score together with Levenshtein distance is utilized in the fine-tuned methodology being developed. Following are steps involved in the proposed framework.

Step 1: Firstly, regarding the RPN value, the Risk prioritized matrix is generated for risk; it is then formulated within n rows and m columns, which is expressed as, (17), shown at the bottom of the next page, where, the degree of confidence is specified as $A_{11}, B_{11}, C_{11}, D_{11}$, the maximum value of interval value

fuzzy set is signified as B_{11}^-, B_{11}^+, the minimum value of fuzzy sets is illustrated as Ψ_{11}, the uncertain linguistic variable is proffered as $\beta\varphi_{11}$.

Step 2: Here, FTTF-TOPSIS builds the risk prioritized matrix $\aleph = \left[\forall_{ij}\right]$ regarding the decision matrix, (18), as shown at the bottom of the next page.

Step 3: Next, the Risk prioritized matrix is produced utilizing its corresponding weights. The weight vector $W = (\omega_1, \omega_2, \omega_3, \ldots..\omega_n)$gathered as of the isolated weights $\omega_j\,(j = 1, 2, 3, \ldots .n)$ for every single attribute gratifying $\sum_{j=1}^{n} W_j = 1$. The weighted normalized value is illustrated as,

$$A_j = \forall_{ij}\omega_j \tag{19}$$

Step 4: The Positive Ideal Solution (PIS) $\left(\alpha_i^+\right)$ along with the Negative Ideal Solution (NIS) $\left(\alpha_i^-\right)$ is calculated after formulating the Risk Prioritized matrix as follows.

$$\begin{aligned} \alpha_i^+ = &\{\beta\varphi_1\left[A_1, B_1, C_1, D_1\right], \alpha\varphi_2 \\ &\times \left[A_2, B_2, C_2, D_2\right]\cdots\cdots\beta\varphi_n\left[A_n, B_n, C_n, D_n\right] \\ &\times \left\{\left\langle\left[B_1^-, \Psi_1\right], \left[B_2^-, \Psi_2\right]\cdots\left[B_n^-, \Psi_m\right]\right\rangle\right\}\} \\ = &\max_i \beta\varphi_{ij}, \max_i\left(A_{ij}, B_{ij}, C_{ij}, D_{ij}\right), \left\{\max_i\left(B_1^+\right)\right\} \\ &\left\{\min_i\left(\Psi_i\right)\right\} \end{aligned} \tag{20}$$

$$\begin{aligned} \alpha_i^- = &\{\beta\varphi_1\left[A_1, B_1, C_1, D_1\right], \alpha\varphi_2 \\ &\times \left[A_2, B_2, C_2, D_2\right]\cdots\cdots\beta\varphi_n\left[A_n, B_n, C_n, D_n\right], \\ &\times \left\{\left\langle\left[B_1^-, \Psi_1\right], \left[B_2^-, \Psi_2\right]\cdots\left[B_n^-, \Psi_n\right]\right\rangle\right\}\} \\ = &\min_i \beta\varphi_{ij}, \min_i\left(A_{ij}, B_{ij}, C_{ij}, D_{ij}\right), \left\{\min_i\left(B_1^+\right)\right\} \\ &\left\{\max_i\left(\Psi_i\right)\right\} \end{aligned} \tag{21}$$

Step 5: In this, by deploying the n-dimensional Levenshtein distance, the separation measures are gauged. The transposition of '2' adjacent candidates beside deletion, insertion, along with substitution is offered by the Levenshtein distance. The separation of every single candidate as of the trapezoidal linguistic cubic PIS

$l_i^+\left\langle\left[A^-, A^+\right], \Theta\right\rangle$ is formulated as, (22) and (23), shown at the bottom of the next page.

Step 6: The Relative Closeness (RC) to the ideal solution is measured here. This evolution figures out the RC to an ideal solution as,

$$\Gamma_i = \frac{l_i^-\left\langle\left[B^-, B^+\right], \Psi\right\rangle}{l_i^-\left\langle\left[B^-, B^+\right], \Psi\right\rangle + l_i^+\left\langle\left[B^-, B^+\right], \Psi\right\rangle} \tag{24}$$

Step 7: Here, regarding the RC coefficient, the strategies' ranking occurs.

Lastly, the most impacted RFs on the industries are discovered by the ranking procedure. Algorithm 1 exhibits, the proposed FTTF-TOPSIS's pseudo-code.

D. RISK REDUCTION

Frequency reducing along with impact reducing activities and their amalgamation are included in the process of risk reduction. The measures may be operational, technical, along with organizational in nature. Regarding broad analysis in which the risk aspects are pondered, the sorts of measures are selected in general. To monitor the total effect of the measure on the risk, the emphasis should be adopted. The feasible coupling betwixt risk-reducing measures should interact overtly with the decision-makers if alternative measures are proposed. Whilst selecting which measures are instigated along with developed into an accident event, the measures that mitigate the frequency for a hazardous situation are prioritized. Measures should be considered for the design of ERP projects to mitigate any impacts. The reliability and the probability of documenting along with verifying the determined extent of risk reduction are regarded whilst choosing risk-reducing measures. When analogized with the frequency reducing measures, the consequence reducing measures possess higher reliability, particularly for the operating criteria. The current phase in the activity, available technology, and the outcomes of cost-benefit evaluation are the factors on which the probability of implementing particular risk-reducing measures relies. Thus, in association with such aspects, the option of risk-reducing measures can be explicated.

IV. RESULTS AND DISCUSSION

To prioritize the risk to decrease the likelihood of risk, the FMEA is evaluated centered on the ranking approaches. For examining the FMEA, the study has chosen 7 FMs $(F_M^1, F_M^2, F_M^3, F_M^4, F_M^5, F_M^6, F_M^7)$. Every mode illustrates definite risks like organizational and management risk, which includes bad cultural readiness, bad organizational maturity level, insufficient training, insufficient communication system, etc. The technological risk encompasses poor technical infrastructure, incorrect package selection, etc. The processes risk includes commitment issues with the leadership team, insufficient budget, deprived project creep management, etc.

$$RPN(P) = \begin{bmatrix} FMs/RPN & \Gamma & \theta & D\mathfrak{R}_D U_R & C_S \\ F_M^1 & A_{11}, B_{11}, C_{11}, D_{11} & A_{12}, B_{12}, C_{1,}, D_{12} & \cdots\cdots\cdots & A_{16}, B_{16}, C_{16} D_{16} \\ \vdots & \vdots & \vdots & \vdots\ \vdots\ \vdots & \vdots \\ F_l^W & A_{l11}, B_{N1}, C_{N1}, D_{111} & A_{N2}, B_{N2}, C_{N2}, D_{N2} & \cdots\cdots\cdots & A_{VM}, B_{VM}, C_{NH}, D_{NM} \end{bmatrix} \tag{16}$$

$$\forall_{DM} = \begin{bmatrix} \beta\varphi_{11}\left[A_{11}, B_{11}, C_{11}, D_{11}\right]\left\langle\left[B_{11}^-, B_{11}^+\right], \Psi_{11}\right\rangle & \cdots & \cdots & \beta\varphi_{n1}\left[A_{n1}, B_{n1}, C_{n1}, D_{n1}\right]\left\langle\left[B_{n1}^-, B_{n1}^+\right], \Psi_{1n}\right\rangle \\ \beta\varphi_{22}\left[A_{22}, B_{22}, C_{22}, D_{22}\right]\left\langle\left[B_{22}^-, B_{22}^+\right], \Psi_{22}\right\rangle & \cdots & \cdots & \beta\varphi_{n2}\left[A_{n2}, B_{n2}, C_{n2}, D_{n2}\right]\left\langle\left[B_{n2}^-, B_{n2}^+\right], \Psi_{2n}\right\rangle \\ \vdots & \vdots & \vdots & \vdots \\ \beta\varphi_{m1}\left[A_{m1}, B_{m1}, C_{m1}, D_{m1}\right]\left\langle\left[B_{m1}^-, B_{m1}^+\right], \Psi_{m1}\right\rangle & \cdots & \cdots & \beta\varphi_{mn}\left[A_{mn}, B_{mn}, C_{mn}, D_{mn}\right]\left\langle\left[B_{mn}^-, B_{mn}^+\right], \Psi_{mn}\right\rangle \end{bmatrix} \tag{17}$$

$$\forall_{ij} = \begin{bmatrix} \dfrac{\beta\varphi - \sum_{i=1}^{n}(\alpha\varphi)_{ij}}{\sigma(\beta\varphi)} \left[\dfrac{A - \sum_{i=1}^{n}(A)_{ij}}{\sigma(A)}, \dfrac{B - \sum_{i=1}^{n}(B)_{ij}}{\sigma(B)}, \dfrac{C - \sum_{i=1}^{n}(C)_{ij}}{\sigma(C)}, \dfrac{D - \sum_{i=1}^{n}(D)_{ij}}{\sigma(D)}\right] \\ \left\langle \left[\dfrac{B^- - \sum_{i=1}^{n}(B^-)_{ij}}{\sigma(B^-)}, \dfrac{B^+ - \sum_{i=1}^{n}(B^+)_{ij}}{\sigma(B^+)}\right] \dfrac{\Psi - \sum_{i=1}^{n}(\Psi)_{ij}}{\sigma(\Psi)} \right\rangle \\ , \end{bmatrix} \tag{18}$$

$$l_i^+\left\langle\left[B^-, B^+\right], \Psi\right\rangle = \begin{cases} \left|\left|\beta\varphi_{ij} - \varphi_j\right|, \left|A_{ij} - A_j\right|\right| & if \left|\left|B_{ij} - B_j\right| + \left|C_{ij} - C_j\right|\right| = 0 \\ \left|B_{ij} - B_j\right| + \left|C_{ij} - C_j\right| & if \left|\left|\beta\varphi_{ij} - \varphi_j\right|, \left|A_{ij} - A_j\right|\right| = 0 \\ lev\left(tail\left|\beta\varphi_{ij} - \varphi_j\right|, \left|A_{ij} - A_j\right|, tail\left|B_{ij} - B_j\right| + \left|C_{ij} - C_j\right|\right) & if\ B^-[0] = B^+[0] \\ 1 + min \begin{cases} lev\left(tail\left(B^-\right), B^+\right) \\ lev\left(\left(B^-\right), tail\left(B^+\right)\right) \\ lev\left(tail\left(B^-\right), tail\left(B^+\right)\right) \end{cases} & otherwise \end{cases} \tag{22}$$

$$l_i^-\left\langle\left[B^-, B^+\right], \Psi\right\rangle = \begin{cases} \left|\left|\beta\varphi_{ij} - \varphi_j\right|, \left|A_{ij} - A_j\right|\right| & if \left|\left|B_{ij} - B_j\right| + \left|C_{ij} - C_j\right|\right| = 0 \\ \left|B_{ij} - B_j\right| + \left|C_{ij} - C_j\right| & if \left|\left|\beta\varphi_{ij} - \varphi_j\right|, \left|A_{ij} - A_j\right|\right| = 0 \\ lev\left(tail\left|\beta\varphi_{ij} - \varphi_j\right|, \left|A_{ij} - A_j\right|, tail\left|B_{ij} - B_j\right| + \left|C_{ij} - C_j\right|\right) & if\ B^-[0] = B^+[0] \\ 1 + max \begin{cases} lev\left(tail\left(B^-\right), B^+\right) \\ lev\left(\left(B^-\right), tail\left(B^+\right)\right) \\ lev\left(tail\left(B^-\right), tail\left(B^+\right)\right) \end{cases} & otherwise \end{cases} \tag{23}$$

Algorithm 1 : Pseudo Code for Proposed FTTF-TOPSIS

Input: RPN Matrix based on $RPN\ [\mathbf{P}] = \Gamma \times \Theta \times D \times \Re_D \times U_R \times C_s$

Output: Risk prioritization

Begin
  Create a decision matrix $\forall_{DM}$
    For i in $\forall_{DM}$
      Calculate RPN Matrix $\aleph = [\forall_{ij}]$
    End For
    Calculate Z-Score based Normalized weight matrix
    For $\forall_{ij}$ in $\forall_{DM}$
      $A_j = \forall_{ij}\omega_j$
    End For
    Determine the positive (α_i^+) and negative ideal solution (α_i^-)
    For A_j in $\forall_{DM}$ do
    Calculate (α_i^-) and (α_i^+)
    End For
    Calculate separation from l_i^+ and l_i^-
    For A_j in $\forall_{DM}$ do
    Calculate (α_i^-) and (α_i^+)
    End For
    Determine relative closeness
    For A_j in $\forall_{DM}$ do
    $\Gamma_i = \frac{l_i^- \langle [B^-, B^+], \Psi \rangle}{l_i^- \langle [B^-, B^+], \Psi \rangle + l_i^+ \langle [B^-, B^+], \Psi \rangle}$
    End For
    Rank the Risk
End Begin

The people risk (internal) consists of bad leadership, workforce resistance to alter, so on and people risk (external) involves inefficient consulting services, development errors, etc. Strategic risk includes no apparent targets and objectives, bad ERP implementation plan, etc. Lastly, to appraise the FMEA's feasibility, the fuzzy VIKOR technique, fuzzy TOPSIS, Hybrid COPRAS are implemented to rank the priority and weighed against the acquired outcome.

A. PERFORMANCE ANALYSIS

The FMEA methodology is authenticated centered on the RP utilizing the FTTF-TOPSIS method. To enhance the RPN computation, the FMEA inserts '3' more parameters, like relative dependency, uncertain risk, and cost. The proposed method's RA and RP are listed below.

Table 1 shows assessment information for the 7 FMs under every RI offered by the FMEA team. Table 2 illustrates that the FTTF-TOPSIS method converts the linguistic information gathered from team members into numerical formats. Under HMM, the corresponding linguistic terms for risk value are devised and processed for accurate RPN assessment. The HMM methods aid to decrease data difficulties and provide a data's structured format. It is evident that there is assorted information concerning the data i.e. linguistic terms, which makes it difficult to observe the risk clearly. The numerical conversion aids to undergo a comprehensive risks analysis.

TABLE 1. Linguistic terms and values for Γ, Θ, D, $\Re_D$, U_R and, C_s.

FMs	Γ	Θ	D	$\Re_D$	U_R	C_s
	TM1	TM2	TM3	TM4	TM5	TM6
F_M^1	MH ,MH,H, MH	LH, LH,MH, H	VH,VH,E H,EH	LH,LH,H, MH	L,L,LH, L	L,MH, HL,MH
F_M^2	H,MH, H,MH	ML,L,M H,MH	MH,MH, H,MH	EH, EH,EH, EH	L,ML, MH,M H	MH,MH ,H,MH
F_M^3	H,H,E H,MH	MH,L, ML,MH	H,MH,H, ML	VH,MH, ML,MH	H,VH, MH,H	H,MH, H,VH
F_M^4	VH,H, MH,H	H,VH,M H,ML	ML,MH, ML,L	ML,VL,V L,L	MH,H, ML,ML	ML,ML, ML,L
F_M^5	H,VH, H,H	MH,MH ,H,H	H,H,H,M H	MH,ML, L,VL	L,L,ML ,L	L,L,L,L
F_M^6	H,MH, MH,H	VH,H,H ,H	MH,MH, MH,H	MH,MH, ML,MH	ML,MH ,L,L	L,L,L,V L
F_M^7	VH,H, H,VH	H,H,H, VH	MH,MH, MH,ML	ML,ML, MH,MH	MH,M H,H,H	VH,H,M H,MH

TABLE 2. Linguistic term value obtained by proposed FTTF-TOPSIS method.

Linguistic term	Trapezoidal fuzzy number
Extremely high risk	(1.00,1.00,1.00,1.00)
Very high (VH)	(0.95,0.96,0.98,0.99)
High (H)	(0.90,0.85,0.88,0.92)
Medium high (MH)	(0.63,0.66,0.79,0.82)
Medium (M)	(0.39,0.43,0.59,0.65)
Medium low (ML)	(0.25,0.29,0.39,0.41)
Low (L)	(0.13,0.15,0.18,0.24)
Very low (VL)	(0.01,0.02,0.03,0.04)
Extremely low (EL)	(0.00,0.00,0.00,0.00)

TABLE 3. Decision matrix.

FMs	Γ	Θ	D	$\Re_D$	U_R	C_s
F_M^1	(0.63,0.66, 0.79,0.82)	(0.39,0.43, 0.59,0.65)	(0.95,0.96, 0.98,0.99)	(0.39,0.43, 0.59,0.65)	(0.39,0.43, 0.59,0.65)	(0.39,0.43, 0.59,0.65)
F_M^2	(0.95,0.96, 0.98,0.99)	(0.63,0.66, 0.79,0.82)	(0.90,0.85, 0.88,0.92)	(1.00,1.00, 1.00,1.00	(0.39,0.43, 0.59,0.65)	0.63,0.66,0 .79,0.82)
F_M^3	(0.95,0.96, 0.98,0.99)	(0.63,0.66, 0.79,0.82)	(0.90,0.85, 0.88,0.92)	(0.39,0.43, 0.59,0.65)	(0,36,0.42, 0.58,0.64)	(0.90,0.85, 0.88,0.92)
F_M^4	(0.95,0.96, 0.98,0.99)	(0.90,0.85, 0.88,0.92)	(0.63,0.66, 0.79,0.82)	(0.90,0.85, 0.88,0.92)	(0.39,0.43, 0.59,0.65)	(0.25,0.29, 0.39,0.41)
F_M^5	(0.95,0.96, 0.98,0.99)	(0.63,0.66, 0.79,0.82)	(0.90,0.85, 0.88,0.92)	(0.25,0,29) ,0,39,0,41)	(0.13,0.15, 0.18,0.24)	(0.25,0.29, 0.39,0.41)
F_M^6	(0.95,0.96, 0.98,0.99)	(0.90,0.85, 0.88,0.92)	(0.63,0.66, 0.79,0.82)	(0.90,0.85, 0.88,0.92)	(0.95,0.96, 0.98,0.99)	(0.63,0.66, 0.79,0.82)
F_M^7	(0.90,0.85, 0.88,0.92)	(0.95,0.96, 0.98,0.99)	(0.63,0.66, 0.79,0.82)	(0.39,0.43, 0.59,0.65)	(0.90,0.85, 0.88,0.92)	(0.95,0.96, 0.98,0.99)

The 9 linguistic terms to rate the FM are described in Table 2. Centered on the recognized FMs, FMEA team members are solicited to give in a RA for 6 risk variables, $\Gamma, \Theta, D, \Re_D, U_R, C_s$ by accepting the fuzzy linguistic terms. A decision matrix is established centered on the linguistic term

The decision matrix creation with the relevant linguistic values is indicated in Table 3. The FTTF-TOPSIS method is used to process the values, and the ranking strategy is examined. The FTTF-TOPSIS method is capable of dealing with uncertain RFs and provides an effective ranking plan.

TABLE 4. The risk priority ranking order of FMs.

FMs	$\beta\phi[F_M^N]$	α_i^+	α_i^-	Γ_i	Ranking
F_M^1	1.25	12.34	4.23	0.255	3
F_M^2	7.86	13.45	3.78	0.219	4
F_M^3	5.89	10.24	2.54	0.198	6
F_M^4	6.89	09.87	2.45	0.198	6
F_M^5	5.21	13.45	3.56	0.209	5
F_M^6	8.87	12.44	4.29	0.256	2
F_M^7	8.84	15.64	5.68	0.266	1

TABLE 5. Relative dependency index.

Stages/projects	F_M^1	F_M^2	F_M^3	F_M^4
PROJECT A	0.001	0.0018	0.0019	0.0012
PROJECT B	0.018	0.019	0.011	0.009
PROJECT C	0.028	0.021	0.014	0.0011
PROJECT D	0.021	0.017	0.011	0.008

The ranking is completely centered on the trapezoidal membership function, which improves the lower bound and upper bound limitation to choose risk. With diverse prioritized RPN values, the FTTF-TOPSIS method identifies the FMs' risk implications.

A comprehensive investigation of FTTF-TOPSIS to direct the FMs as per their risk capability is exhibited in Table 4. For FM 7, the method generates the PIS and NIS of 15.64 and 5.68 respectively, and for each ideal solution, it manages to accomplish a RC of 0.266, and it is ranked as a very high risk. FMs 3 and 4 have the lowest risk values, with 0.198 of RC, which is identical for both. Because of the TOPSIS model's fine-tuning, the FTTF-TOPSIS method provides accurate risk estimation. The fine-tuning aids to manage the outliers and uncertain data and do not permit them to disrupt the ranking mechanism i.e. rank reversal. Therefore, the proposed ranking method is extremely effective to rank the risk centered on the RPN value.

Table 5 shows the risk dependency index's highest possible value is 0.028. The entire value of all indexes is comparatively low, implying that several risks discovered were not related to any risk dependencies. For FMs 2 and 3, the risk dependency indexes of every four projects were increasing. Because of the effects of risk response actions, the larger number of risks discovered in the previous phases was deleted on their difficulty levels. The risk dependency effects are influencing the project B risks whilst those risk in the Project had been the slightest influenced. This is due to Project D's system had been the highly damaged, with the greatest number of interfaces amongst the Projects A, B, along with C's systems. But, Project A's system was afflicted the least owing to the less number of interfaces with other devices. Thus, for the FMs, the dependency index was comparatively low.

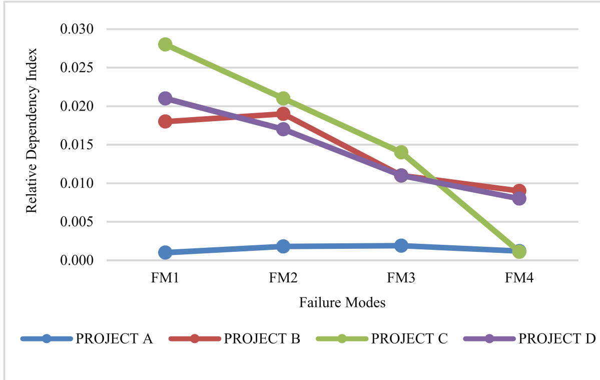

FIGURE 2. Graphical representation of relative dependency index.

TABLE 6. evaluation of FMEA methods based on the coefficient of variation in ranking.

Statistical variables	Hybrid COPRAS Method	Fuzzy VIKOR Method	Fuzzy TOPSIS	Proposed FTTF-TOPSIS
Mean	245.64	78.98	45.67	12.45
Standard deviation	117.85	39.65	27.45	06.54
Coefficient of variation	0.478	0.589	0.667	0.895

TABLE 7. Evaluation of risk ranking results for different FMEA methods.

Techniques/Failure modes	FM 1	FM 2	FM 3	FM 4	FM 5	FM 6	FM 7
Hybrid COPRAS	5	4	7	6	3	1	2
Fuzzy VIKOR Method	1	3	2	5	4	6	7
Fuzzy TOPSIS	7	6	4	5	1	2	3
Proposed FTTF-TOPSIS	3	4	6	6	5	2	1

Fig 2 visually finishes off that the FMEA method focuses on identifying out relative dependency for the risk, which aids to enhance the RPN computation and to get the appropriate preventive measures in the future.

B. COMPARATIVE ANALYSIS

Hybrid Complex Proportional Assessment (HCOPRAS), Fuzzy VlseKriterijumska Optimizacija I Kompromisno Resenje (FVIKOR), and Fuzzy TOPSIS (FTOPSIS) are the prevailing methodologies with which, the obtained ranking outcomes are analogized. Table 6 illustrates the comparative evaluation.

To establish the relative variability amongst '2' or more sample data sets; also, to investigate the partition of a degree of FMs offered by the '3' FMEA methodologies, the coefficient of variation is utilized. The computation outcomes are demonstrated in Table 6. Regarding the partition degree amongst the identified FMs, the recommended methodology surpasses the available HCOPRAS, FTOPSIS, and FVIKOR models. It is observed that the present methodology avoids RF dependence, which brings about a partial ranking of failure types. Whilst avoiding any inter-relationships betwixt

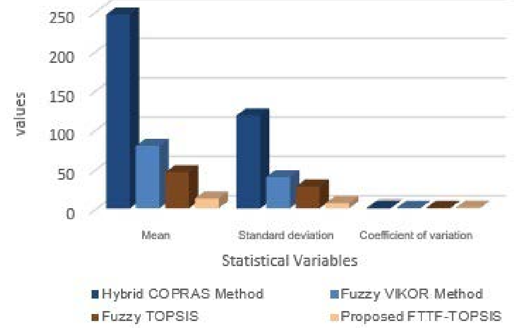

FIGURE 3. Graphical demonstration of the proposed method based on statistical variables.

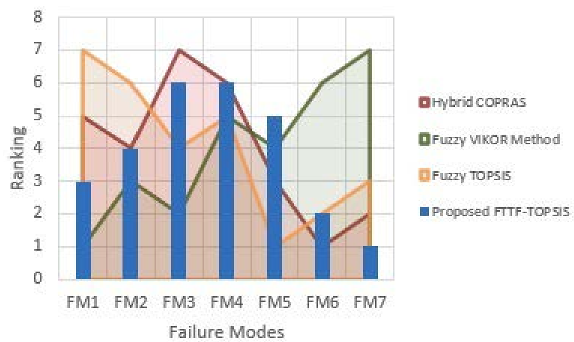

FIGURE 4. Different FMEA method for ranking risk.

any '2' FMs, the FVIKOR analogizes every single FM to the most hazardous one. Consequently, the proposed methodology ponders the Relative Dependence betwixt risks along with ameliorates the outcome.

The proposed ranking strategy's statistical variable assessment was exhibited in Fig 3. The proposed methodology is more strong in prioritizing the risk under uncertain situations along with it has the potential to defeat the existent complications.

From the table, it is established that the same ranking for FM 4 was attained by the prevailing Fuzzy VOKOR along with Fuzzy TOPSIS methodologies; however, a ranking of 6 to the same mode was achieved by the proposed along with the Hybrid COPRAS. Owing to the enhancement made to establish the RPN along with the strategy utilized to rank, a better ranking was achieved by the proposed framework. When analogized with the prevailing methodology, the proposed mechanism, which prioritizes the risk is highly considerable along with credible.

The variation betwixt the ranking strategy implemented by the proposed and the prevailing methodology is demonstrated graphically in Fig 4. The divergences amongst the team members for evaluating the risk are mitigated; in addition, to enhance the RA along with RP properties in FMEA, a pair-wise correlation amongst the risk was performed in the proposed methodology.

V. CONCLUSION

For the identification along with the elimination of risk in numerous fields particularly in ERP implementation, the FMEA, an effective tool is utilized. Thus, the accurate ranking of every single FM is highly significant. In FMEA, the risk pertinent to the detected FMs, causes, along with effects is evaluated; in addition, issues for corrective action are prioritized. However, the RA is highly challenging owing to the difficulties faced in the process of RA together with RP. An FMEA methodology utilizing FTTF-TOPSIS RA has been presented here to conquer the available complications. To calculate RPN, uncertain risk, risk dependency, and cost are regarded as extra parameters in the proposed mechanism. To estimate uncertain risk in conjunction with risk dependency, mathematical modelling like conservative methodology along with SRKM is

employed here. To avoid data complexity, the data preparation focused here by employing the HMM model. Lastly, by wielding the FTTF-TOPSIS methodology, the RP is executed. The evaluation results of Hybrid COPRAS Method, Fuzzy VIKOR Method, Fuzzy TOPSIS and the proposed FTTP-TOPSIS based on the statistical variables showing that mean 245.64, 78.98, 45.67 and 12.45 respectively. Similarly, the standard deviation shows 117.85, 39.65, 27.45 and 06.54 respectively. The coefficient of variation achieves 0.478, 0.589, 0.667 and 0.895 values, respectively. This shows that the proposed methodology has the capacity to manage sudden or uncertain alterations in the risk, adopt numerous attributes-centric decisions making, along with result with the best risk priority. The experiential outcome displayed that by achieving a better ranking strategy together with RDI, the proposed methodology outperforms the prevailing methodologies.

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