Human Resources Management Risks Analysis in Government Organizations: A Fuzzy Approach

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Abstract: - Most research in human resource management has focused on the positive impacts of HRM practices on organizations and communities. However, addressing potential risks identified by management scholars is equally critical. Proactively managing these risks contributes to successful program implementation, reduces long-term costs, enhances workforce sustainability, and supports organizational improvement—empowering managers to make informed decisions. This study evaluates human resource risks in government Organizations using a Fuzzy FMEA approach. After collecting expert responses through questionnaires, risk factor weights were calculated using Fuzzy AHP, followed by risk prioritization. Key findings highlight several areas requiring urgent attention to strengthen organizational effectiveness and fairness.

Keywords: Human Resources Management, Human Resources Management Risks, Fuzzy.

1. Introduction

In recent years, research on human resource management (HRM) has predominantly emphasized the beneficial impacts of HRM practices on both organizations and communities (Chou et al., 2019). These practices contribute to organizational growth and positive societal development. However, despite HRM's significant advantages, it is crucial to consider potential risks—factors that management scholars identify as uncertainties in the external environment. Such risks can particularly influence supply chain management and its objectives (Anwar et al., 2021). Identifying these risks is vital, as it enhances positive outcomes while mitigating negative ones, ultimately affecting key organizational aspects such as time, cost, quality, productivity, and overall performance. Organizations can reduce long-term costs and make more informed, systematic decisions by assessing and evaluating risks. Consequently, risk identification plays a critical role in the successful execution of programs, especially in today's volatile economic climate and amid major disruptions like the COVID-19 pandemic (Hosseini et al., 2021). Overlooking risks—and their potential advantages and disadvantages—can result in investment failures (Cervone, 2006). As a result, businesses increasingly seek to establish structured programs for risk identification and assessment. Given HRM's central role in modern organizations, it must prioritize risk identification and develop strategies to address uncertainties. Due to the substantial impact of these risks on HRM, there is a need for a systematic framework to identify and assess them effectively. This study aims to develop a model for HRM risks using a Fuzzy FMEA approach. The research seeks to establish a structured method for human resource risk management, offering managers a practical framework that integrates HR principles with risk mitigation strategies.

Table 1. Risk Assessment Framework with Fuzzy Logic

Category	Key Points	Supporting Evidence/Implications
HRM Research Focus	Recent studies highlight the positive impacts of HRM practices on organizations and society.	Chou et al. (2019) – Links HRM to organizational growth and societal benefits.
Risk Considerations	Despite benefits, HRM faces external risks that can disrupt supply chains and organizational goals.	Anwar et al. (2021) – Risks introduce uncertainty in management.
Importance of Risk ID	Proactive risk identification enhances positive outcomes and reduces negative effects on time, cost, quality, and productivity.	Cervone (2006) – Ignoring risks leads to investment failures.
Organizational Impact	Risk assessment helps reduce long-term costs and supports data-driven decision-making.	Hosseini et al. (2021) – Critical in volatile/post-pandemic economies.
HRM's Strategic Role	HRM must prioritize risk identification due to its influence on workforce stability.	– Necessitates structured risk management programs.
Proposed Solution	A **Fuzzy FMEA-based model** to systematically assess HRM risks.	– Integrates HR principles with risk mitigation strategies.
Research Objective	Develop a structured HR risk management framework for practical use by managers.	– Aims to bridge HRM and risk assessment methodologies.

2. Theroetical Background

resource management (HRM) is the practice of collaborating with individuals to ensure mutual empowerment, even when adaptation demands acquiring new skills, taking on different responsibilities, and establishing fresh relational dynamics (Mohiuddin et al., 2022). Essentially, HRM seeks to fulfill organizational objectives through key workforce-related functions such as recruitment, training, compensation, and fostering workplace relationships. The field emerged from the human relations movement in the early 20th century, when scholars first explored how strategic workforce management could generate business value. Initially centered on administrative tasks, HRM has since evolved due to globalization, corporate empowerment, technological advancements, and ongoing research. Today, it encompasses strategic responsibilities like mergers and acquisitions, talent management, supply chain considerations, succession planning, and navigating industrial relations amid diverse cultural and competency landscapes. As HRM strategies advanced, organizations began redefining their structures to align more closely with human capital needs. They adopted new terminologies—such as *Talent Management*, *People and Culture*, *Partner Success*, and *Solution Management Center*—to reflect evolving workforce expectations and operational demands. By the 21st century, improvements in transportation and communication further transformed the workforce into a dynamic, interconnected entity. Businesses shifted their perspective, valuing employees as strategic assets rather than replaceable components. This paradigm shift solidified "human resource management" as the defining concept for workforce strategy. Organizations with effective HRM practices often see higher employee and customer satisfaction, alongside greater innovation, stability, productivity, and societal reputation. HRM's role in organizational sustainability is twofold: it must balance short-term cost efficiency and profitability with long-term performance resilience. Sustainable HRM strategies prioritize aligning workforce practices with broader economic, social, and environmental goals, ensuring companies thrive holistically over time.

In today's rapidly evolving business landscape, HR managers must increasingly prioritize risk and uncertainty evaluation—a field gaining significant attention among researchers. This shift is driven by escalating environmental volatility and unpredictable disruptions (Mendonça & Wallace, 2015). The term *risk* originates from the Italian *riscare*, meaning both "uncertain future events" and "to dare," reflecting its dual impact on organizational objectives (Mendonça & Wallace, 2015). The International Organization for Standardization (ISO) defines risk as the effect of external uncertainties on organizational goals, necessitating systematic analysis to guide managerial responses (Chance & Brooks, 2015). Proactive risk assessment ensures program efficacy throughout their lifecycle (Bessis, 2002) by curbing long-term costs and enabling data-driven decisions (Cervone, 2006). Effective risk mitigation hinges on two priorities: control and evaluation (Glendon et al., 2016; Chouhan et al., 2021). Neglecting risk identification can trigger severe consequences, including financial losses and failed investments (Cervone, 2006). Conversely, rigorous assessment optimizes positive outcomes while minimizing adverse effects on time, cost, quality, productivity, and performance (Yamashita et al., 2016). Despite extensive management research, HRM remains vulnerable to multifaceted risks (Meyer et al., 2011). These stem not only from external factors but also from employees' knowledge gaps, skill deficiencies, and personal attributes. Jeynes highlights critical HRM risks, including:

Table 2. HRM Risks and Supporting Literature

Risk Category	Specific Risk	References
Talent Management	Employee retention challenges	Li et al. (2017)
	Recruitment deficiencies	Hotho et al. (2020); Kumar & Raja (2014)
	Training inadequacies	Kumar & Raja (2014); Storey (2014)
Workplace Environment	Ethical violations	Meyer et al. (2011); Oborilová et al. (2015)
	Organizational injustice	Jones (2013)
	Health and wellbeing concerns	Glendon et al. (2016)
Structural/Operational	Regulatory constraints	Bitsch et al. (2006)
	Leadership support gaps	Oborilová et al. (2015)
	Compensation issues	Oborilová et al. (2015)
	Financial constraints	Huber & Scheytt (2013)
	Strategic planning failures	Berman et al. (2019)

FMEA serves as a systematic methodology designed to identify potential system or process failures before they occur (Tooranloo & Sadat Ayatollah, 2016;). As a proactive risk management tool, it helps prevent system malfunctions by evaluating three critical parameters: Occurrence (O) - the probability of failure, Severity (S) - the potential impact of failure, and Detectability (D) - the ability to identify risks before they manifest (Rafie & Samimi Namin, 2015). These components collectively determine the significance of identified risks (Dağsuyu et al., 2016).

Originally developed for industrial applications, FMEA provides organizations with a structured framework to detect vulnerabilities, assess their implications, and implement preventive measures. When properly executed, this technique yields safer operations, enhanced quality control, and more efficient processes (Yang & Wang, 2015).

The conventional FMEA approach employs a numerical scale (1-10) to rate each risk factor, with the composite Risk Priority Number (RPN) calculated through the formula: RPN = O × S × D (Rafie & Samimi Namin, 2015). However, the inherent subjectivity in assessing these parameters has prompted researchers to integrate fuzzy logic into FMEA methodologies.

Several innovative approaches have emerged to address evaluation uncertainties:

1. Bowles and Pelaez (1995) pioneered a fuzzy logic-based system that prioritizes failures using linguistic variables for O, S, and D ratings, with risk relationships established through expert judgment (Bowles & Peláez, 1995)
2. Garcia et al. (2005) developed a hybrid model combining fuzzy data envelopment analysis with fuzzy sets for failure mode classification (Garcia & Schirru, 2005)

3. Tooranloo and Ayatollah (2016) incorporated Intuitionistic Fuzzy Set theory into their FMEA framework (Tooranloo & sadat Ayatollah, 2016)
4. Chen and Kuo (2009) introduced a fuzzy RPN calculation method using Fuzzy Ordered Weighted Geometric Averaging (FOWGA) (L.-H. Chen & Ko, 2009)

Advanced computational techniques such as Alpha-cut sets, linear programming models, and defuzzification processes enable precise ranking of failure modes through fuzzy RPN calculations. Kutlu and Ekmekcioglu (2012) further enhanced the methodology by integrating TOPSIS and AHP within a fuzzy environment - using AHP to establish risk factor weights and TOPSIS to prioritize failure modes (Kutlu & Ekmekçioğlu, 201).

Interval type-2 fuzzy sets

Zadeh (1975) introduced type-2 fuzzy sets to develop fuzzy sets (Zadeh, 1975). Type-2 fuzzy sets have fuzzy membership degrees; hence, they are also called the fuzzy-fuzzy sets, which can reduce the effect and model the uncertainties while encountering them (Coupland & John, 2008). The Type-2 fuzzy set is used when encountering linguistic uncertainty and provides more information than the Type-1 fuzzy set. Type-1 fuzzy set is a first-order approximation of uncertainty; and the Type-2 fuzzy set is the second-order approximation of uncertainty (Mendel, 2007). Type-2 fuzzy sets have better performance in reducing the effect of uncertainty in fuzzy laws (Arjomandi *et al.*, 2007). In addition to the reduced effect of uncertainty in fuzzy laws, it can model the linguistic uncertainties and data effectively due to the fuzzy membership functions in type-2 fuzzy sets (Karnik *et al.*, 1999). Mendel and Liu (2006) provide complete explanations of the second type of fuzzy numbers.

3. The applied approach

The used approach is summarized in table 3:

Table 3. Structured Approach to HR Risk Evaluation: Components and Implementation Steps

Component	Description	Key Details
Objective	Develop a structured risk assessment methodology for HRM.	Combines FMEA (risk identification) and Type-2 fuzzy logic (uncertainty handling).
Core Methodology	Integration of FMEA and Interval Type-2 Fuzzy Logic.	Addresses imprecision in expert judgments.
Phase 1: Fuzzy AHP	Assign weights to HRM risk factors using Interval Type-2 Fuzzy AHP.	Based on Ting (2016).
Step 1	Construct pairwise comparison matrix.	Experts compare risk factors using linguistic terms.
Output	Prioritized list of HRM risks with fuzzy-weighted scores.	Enables data-driven decision-making.

Table 4. Type-2 trapezoidal fuzzy number linguistic variables (Kahraman, Öztayşi, *et al.*, 2014)

Linguistic variables	**Trapezoidal interval type-2 fuzzy scales**
Absolutely Strong	(6,8,9,9;2,1) (6.2,8.2,8.8,9;0.8,1.8)
Very Strong	(4,6,8,9;1,1) (5.2,6.2,7.8,8.8;0.8,0.8)
Fa irly Strong	(3,4,6,7;1,1) (3.3,4.2,5.8,6.8;0.8,0.8)
Slightly Strong	(1,2,4,5;1,1) (1.2,2.2,3.8,4.8;0.8,0.8)
Exactly Equal	(1,1,1,1;1,1) (1,1,1,1;1,1)

In the mentioned table, the reverse type-2 trapezoidal fuzzy number is obtained using Eq. (8).

Matrix $\tilde{\tilde{A}}$ is obtained for the factors using Eq. (8).

$$\tilde{\tilde{A}} = \begin{bmatrix} 1 & \tilde{\tilde{a}}_{12} & \cdots & \tilde{\tilde{a}}_{1n} \\ \tilde{\tilde{a}}_{21} & 1 & \cdots & \tilde{\tilde{a}}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{\tilde{a}}_{n1} & \tilde{\tilde{a}}_{n2} & \cdots & 1 \end{bmatrix} = \begin{bmatrix} 1 & \tilde{\tilde{a}}_{12} & \cdots & \tilde{\tilde{a}}_{1n} \\ 1/\tilde{\tilde{a}}_{12} & 1 & \cdots & \tilde{\tilde{a}}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/\tilde{\tilde{a}}_{1n} & 1/\tilde{\tilde{a}}_{2n} & \cdots & 1 \end{bmatrix} \tag{8}$$

Where

$$\frac{1}{\tilde{\tilde{a}}} = \left(\left(\frac{1}{a_{14}^u}, \frac{1}{a_{13}^u}, \frac{1}{a_{12}^u}, \frac{1}{a_{11}^u}; H_1\left(a_{12}^u\right), H_2\left(a_{13}^u\right)\right), \left(\frac{1}{a_{24}^l}, \frac{1}{a_{23}^l}, \frac{1}{a_{22}^l}, \frac{1}{a_{21}^l}; H_1\left(a_{12}^l\right), H_2\left(a_{13}^l\right)\right)\right)$$

Step 2. Checking the compatibility of the pair-wise comparison matrix:

If we have a positive reciprocal matrix, then the second type of fuzzy positive reciprocal matrix is also compatible. As a result, we first convert the second type of fuzzy numbers to definite numbers using equation 9 and then calculate the incompatibility rate (Kahraman, ßar, *et al.*, 2014).

$$E(U) = DTraT = \frac{1}{2}\left(\frac{(U_u - L_u) + (\beta_u.m_{1u} - L_u) + (\alpha_u.m_{2u} - L_u)}{4} + L_u + \frac{(U_l - L_l) + (\beta_l.m_{1l} - L_l) + (\alpha_l.m_{2l} - L_l)}{4} + L_l\right) \tag{9}$$

Step 3. Integrating the Experts' matrix of pair-wise comparisons: Experts' pair-wise comparison matrix is integrated using Eq. (10).

$$\tilde{\tilde{r}}_{ij} = \left[\tilde{\tilde{a}}_{ij1} \otimes \tilde{\tilde{a}}_{ij2} \otimes \cdots \otimes \tilde{\tilde{a}}_{ijk}\right]^{\frac{1}{k}} \qquad i, j = O, S, D \tag{10}$$

Where K denotes the number of decision-makers.

Step 4. The geometric mean of each row is calculated, and then the fuzzy weights are computed by normalization. The geometric mean of each row $\tilde{\tilde{r}}_i$ is calculated as follows:

$$\tilde{\tilde{r}}_i = \left[\tilde{\tilde{a}}_{iO} \otimes \tilde{\tilde{a}}_{iS} \otimes \tilde{\tilde{a}}_{iD}\right]^{\frac{1}{3}} \qquad i = O, S, D \tag{11}$$

Where

$$\sqrt[3]{\tilde{\tilde{a}}_{ij}} = \left(\left(\sqrt[3]{\tilde{\tilde{a}}_{ij1}^u}, \sqrt[3]{\tilde{\tilde{a}}_{ij2}^u}, \sqrt[3]{\tilde{\tilde{a}}_{ij3}^u}, \sqrt[3]{\tilde{\tilde{a}}_{ij4}^u}; H_1^u\left(a_{ij}\right), H_1^u\left(a_{ij}\right)\right), \left(\sqrt[3]{\tilde{\tilde{a}}_{ij1}^l}, \sqrt[3]{\tilde{\tilde{a}}_{ij2}^l}, \sqrt[3]{\tilde{\tilde{a}}_{ij3}^l}, \sqrt[3]{\tilde{\tilde{a}}_{ij4}^l}; H_1^l\left(a_{ij}\right), H_1^l\left(a_{ij}\right)\right)\right)$$

Step 5. Calculating the fuzzy weights: the fuzzy weight of each factor is obtained from Eq. (12).

$$\tilde{\tilde{w}}_j = \tilde{\tilde{r}}_j \otimes \left(\tilde{\tilde{r}}_O \oplus \tilde{\tilde{r}}_S \oplus \tilde{\tilde{r}}_D\right)^{-1} \tag{12}$$

Where

$$\frac{\tilde{\tilde{a}}}{\tilde{\tilde{b}}} = \left(\begin{array}{l} \left(\frac{a_1^u}{b_4^u}, \frac{a_2^u}{b_3^u}, \frac{a_3^u}{b_2^u}, \frac{a_4^u}{b_1^u}; \min\left(H_1^u(a), H_1^u(b)\right), \min\left(H_2^u(a), H_2^u(b)\right) \right), \\ \left(\frac{a_1^l}{b_4^l}, \frac{a_2^l}{b_3^l}, \frac{a_3^l}{b_2^l}, \frac{a_4^l}{b_1^l}; \min\left(H_1^l(a), H_1^l(b)\right), \min\left(H_2^l(a), H_2^l(b)\right) \right) \end{array} \right)$$

Step 6. Defuzzifying and normalizing the fuzzy weights: Using Eq. (13), the defuzzified weights of factors are obtained(Kahraman, ßar, *et al.*, 2014).

$$E(U) = DTraT = \frac{1}{2}\left(\begin{array}{l} \frac{(U_u - L_u) + (\beta_u . m_{1u} - L_u) + (\alpha_u . m_{2u} - L_u)}{4} + L_u \\ + \frac{(U_l - L_l) + (\beta_l . m_{1l} - L_l) + (\alpha_l . m_{2l} - L_l)}{4} + L_l \end{array} \right) \tag{13}$$

Second phase. Prioritizing the HRM risks through the interval type-2 fuzzy TOPSIS.

The HRM risks are prioritized through type-2 fuzzy TOPSIS after determining the weights of risk factors. Based on type-2 fuzzy TOPSIS(S.-M. Chen & Lee, 2010), the stages of this phase are described as follows:

Step 1. Construct the decision matrix Y_p of the P^{th} decision-maker and construct the average decision matrix $\bar{Y}$, respectively, shown as follows:

$$Y_p = (f_{ij}^P)_{m\times n} = \begin{array}{c} \\ f_1 \\ f_2 \\ \vdots \\ f_m \end{array} \begin{array}{c} \begin{array}{ccc} O & S & D \end{array} \\ \begin{bmatrix} \tilde{\tilde{f}}_{11}^p & \tilde{\tilde{f}}_{12}^p & \tilde{\tilde{f}}_{13}^p \\ \tilde{\tilde{f}}_{21}^p & \tilde{\tilde{f}}_{22}^p & \tilde{\tilde{f}}_{23}^p \\ \vdots & \vdots & \vdots \\ \tilde{\tilde{f}}_{m1}^p & \tilde{\tilde{f}}_{m2}^p & \tilde{\tilde{f}}_{m3}^p \end{bmatrix} \end{array} \tag{14}$$

$$\bar{Y} = (\tilde{\tilde{f}}_{ij})_{m\times n}$$

Where $\tilde{\tilde{f}}_{ij} = \left(\frac{\tilde{\tilde{f}}_{ij}^1 \oplus \tilde{\tilde{f}}_{ij}^2 \oplus \cdots \oplus \tilde{\tilde{f}}_{ij}^k}{K} \right),$

$\tilde{\tilde{f}}_{ij}$ is an interval type-2 fuzzy set, $1 \le i \le m$, $i = O, S, D$, $1 \le P \le k$, and K denotes the number of decision-makers.

Step 2. Determining the weight of risk factors: the weight of risk factors has been determined using the interval type-2 fuzzy AHP in the first phase.

Step 3. Construct the weighted decision matrix $\bar{Y}_w$.

$$\bar{Y}_w = \left(\tilde{\tilde{V}}_{ij}\right)_{m\times n} = \begin{array}{c} \\ f_1 \\ f_2 \\ \vdots \\ f_m \end{array} \begin{array}{c} \begin{array}{ccc} O & S & D \end{array} \\ \begin{bmatrix} \tilde{\tilde{V}}_{11} & \tilde{\tilde{V}}_{12} & \tilde{\tilde{V}}_{13} \\ \tilde{\tilde{V}}_{21} & \tilde{\tilde{V}}_{22} & \tilde{\tilde{V}}_{23} \\ \vdots & \vdots & \vdots \\ \tilde{\tilde{V}}_{m1} & \tilde{\tilde{V}}_{m2} & \tilde{\tilde{V}}_{m3} \end{bmatrix} \end{array} \tag{15}$$

Where $\tilde{\tilde{V}} = \tilde{\tilde{w}} \otimes \tilde{\tilde{f}}_{ij}, 1 \le i \le m$ and $j = O, S, D$

Step 4. Based on Eq. (16), calculate the ranking value $Rank(\tilde{\tilde{V}}_{ij})$ of the interval type-2 fuzzy set $\tilde{\tilde{V}}_{ij}$, where $j = O,S,D$. Construct the ranking weighted decision matrix $\bar{Y}_w^*$.

$\bar{Y}_w^* = (Rank(\tilde{\tilde{V}}_{ij}))_{m \times n}$, Where $1 \le i \le m$ and $j = O,S,D$.

The ranking value $Rank(\tilde{\tilde{A}}_i)$ of the trapezoidal interval type-2 fuzzy set $\tilde{\tilde{A}}_i$ defined as follows (Lee & Chen, 2008):

$$\begin{aligned} Rank(\tilde{\tilde{A}}_i) &= M_1(A_i^U)+M_1(A_i^L)+M_2(A_i^U)+M_2(A_i^L)+M_3(A_i^U)+M_3(A_i^L) \\ &-\frac{1}{4}\left(S_1(A_i^U)+S_1(A_i^L)+S_2(A_i^U)+S_2(A_i^L)+S_3(A_i^U)+S_3(A_i^L)+S_4(A_i^U)+S_4(A_i^L)\right) \\ &+H_1(A_i^U)+H_1(A_i^L)+H_2(A_i^U)+H_2(A_i^L) \end{aligned} \tag{16}$$

Where $M_P(A_i^j)$ denotes the average of the elements a_{ip}^j and $a_{i(p+1)}^j$, $M_P(A_i^j) = \frac{\left(a_{ip}^j + a_{i(p+1)}^j\right)}{2}$, $1 \le P \le 3$, $S_q(A_i^j)$ denotes the standard deviation of the elements a_{ip}^j and $a_{i(p+1)}^j$,

$S_q(A_i^j) = \sqrt{\frac{1}{2}\sum_{k+q}^{q+1}\left(a_{ik}^j - \frac{1}{2}\sum_{k=q}^{q+1} a_{ik}^j\right)^2}$, $1 \le q \le 3$, $S_4(A_i^j)$ denotes the standard deviation of the elements $a_{i1}^j, a_{i2}^j, a_{i3}^j, a_{i4}^j$, $S_4(A_i^j) = \sqrt{\frac{1}{4}\sum_{k=1}^{4}\left(a_{ik}^j - \frac{1}{4}\sum_{k=1}^{4} a_{ik}^j\right)^2}$, $H_P(A_i^j)$ denotes the membership value of the element $a_{i(p+1)}^j$ in the trapezoidal membership function A_i^j, $1 \le P \le 2$, $j \in \{U, L\}$, and $1 \le i \le n$.

In Eq. (16), the summation of $M_1(A_i^U)$, $M_1(A_i^L)$, $M_2(A_i^U)$, $M_2(A_i^L)$, $M_3(A_i^U)$, $M_3(A_i^L)$, $H_1(A_i^U)$, $H_1(A_i^L)$, $H_2(A_i^U)$ and $H_2(A_i^L)$ is called the basic ranking score, where we deduct the average of $S_1(A_i^U)$, $S_1(A_i^L)$, $S_2(A_i^U)$, $S_2(A_i^L)$, $S_3(A_i^U)$, $S_3(A_i^L)$, $S_4(A_i^U)$ and $S_4(A_i^L)$ from the basic ranking score to give the dispersive interval type-2 fuzzy set a penalty, where $1 \le i \le n$. .

Step 5. Determine the positive ideal solution $X^+ = (V_O^+, V_S^+, V_D^+)$ and the negative ideal solution $X^- = (V_O^-, V_S^-, V_D^-)$, where

$$V_i^+ = \begin{cases} \max\limits_{1 \le j \le n}\{Rank(\tilde{\tilde{v}}_{ij})\}, & if \quad f_i \in F_1 \\ \max\limits_{1 \le j \le n}\{Rank(\tilde{\tilde{v}}_{ij})\}, & if \quad f_i \in F_2 \end{cases} \tag{17}$$

And

$$V_i^- = \begin{cases} \min\limits_{1 \le j \le n}\{Rank(\tilde{\tilde{v}}_{ij})\}, & if \quad f_i \in F_1 \\ \min\limits_{1 \le j \le n}\{Rank(\tilde{\tilde{v}}_{ij})\}, & if \quad f_i \in F_2 \end{cases} \tag{18}$$

where F_1 denotes the set of benefit attributes, F_2 denotes the set of cost attributes, and $1 \le i \le m$.

Step 6. Calculate the distance $d^+(x_j)$ between each alternative x_j and the positive ideal solution x^+, shown as follows:

$$d^{+}(x_j)=\sqrt{\sum_{i=1}^{m}\left(Rank(\tilde{\tilde{v}}_{ij})-v_i^{+}\right)^2} \tag{19}$$

Where $1\leq j\leq n$. Calculate the distanceand the negative ideal solution x_j between each alternative $d^{-}(x_j)$, shown as follows: X^{-}

$$d^{-}(x_j)=\sqrt{\sum_{i=1}^{m}\left(Rank(\tilde{\tilde{v}}_{ij})-v_i^{-}\right)^2} \tag{20}$$

Where $1\leq j\leq n$.

Step 7. Calculate the relative degree of closeness $C(x_j)$ of x_j with respect to the positive ideal solution X^{+} , shown as follows:

$$C(x_j)=\frac{d^{-}(x_j)}{d^{+}(x_j)+d^{-}(x_j)} \tag{21}$$

Where $1\leq j\leq n$.

Step 8. Sort the values of $C(x_j)$ in a descending sequence, where $1\leq j\leq n$. The larger the value of $C(x_j)$, the higher the preference of the alternative x_j , where $1\leq j\leq n$.

4. Results

This section outlines the practical application of the proposed algorithm for analyzing HRM risks with a type-2 fuzzy FMEA approach. The necessary data for testing the model was gathered from government agencies.

Through expert interviews and surveys, 12 key HRM risks—identified from existing literature (see Table 2)—were selected for evaluation within these organizations. The findings from applying the algorithm to assess these risks are detailed below:

Phase 1: Calculating Risk Factor Weights with Type-2 Fuzzy AHP Approach

Step 1: Building the Pairwise Comparison Matrix with Type-2 Fuzzy Values
A structured questionnaire was developed to compare risk factors in pairs and distributed to specialists working in government agencies. Once responses were gathered, the linguistic terms provided by experts were converted into type-2 fuzzy numerical values using the conversion scales.

Step 2: Verifying Matrix Consistency

To ensure the reliability of the pairwise comparison matrices, the fuzzy values were first converted into crisp numbers using Equation (12). Next, the consistency ratio for each matrix was examined. The analysis confirmed that all eight matrices had an acceptable consistency ratio below the threshold of 0.1.

Step 3: Combining Expert Judgments

The individual pairwise comparison matrices from different experts were merged into a single aggregated matrix using Equation (10). The final consolidated matrix, representing the combined expert inputs, is displayed in Table 5.

Table 5. Aggregated Pair-wise comparison matrix

	O	*S*	*D*
O	((1,1,1,1;1,1),(1,1,1,1;0.8,0.8))	((3,4,6,7;1,1),(3.2,4.2,5.8,6.8;0.8, 0.8))	((5,6,8,9;1,1),(5.2,6.2,7.8, 8.8;0.8,0.8))
S	((0.14,0.17,0.25,0.33;1,1),(0.15,0.17,0 .24,0.31;0.8,0.8))	((1,1,1,1;1,1),(1,1,1,1;0.8,0.8))	((1,2,4,5;1,1),(1.2,2.2,3.8, 4.8;0.8,0.8))
D	((0.11,0.13,0.17,0.2;1,1),(0.11,0.13,0. 16,0.19;0.8,0.8))	((0.2,0.25,0.5,1;1,1),(0.21,0.26,0.4 5,0.83;0.8,0.8))	((1,1,1,1;1,1),(1,1,1,1;0.8, 0.8))

Step 4. The geometric mean of each row of defuzzified pair-wise comparison matrices is calculated using Eq. (11). Table 5 is used for the representative calculations, which includes the type-2 fuzzy sets of pair-wise comparisons for the criteria. The results show in table 6.

Table 6. The geometric mean of risk factors

O	((1.97,2.21,2.63,2.82;1,1),(2.02,2.26,2.59,2.78;0.85,0.85))
S	((0.61,0.76,1,1.13;1,1),(0.65,0.78,0.98,1.1;0.85,0.85))
D	((0.39,0.42,0.54,0.67;1,1),(0.39,0.43,0.52,0.63;0.85,0.85))

Step 5: Calculating the type-2 fuzzy weights: Using Eq. (12), the fuzzy weights of the risk factors were determined. The calculated values for the risk factors are depicted in table 7.

Table 7. The fuzzy and certain weights

O	((0.426,0.531,0.774,0.95;1,1),(0.447,0.552,0.747,0.909;0.8,0.8))
S	((0.132,0.183,0.294,0.382;1,1),(0.144,0.191,0.282,0.361;0.8,0.8))
D	((0.083,0.102,0.159,0.226;1,1),(0.086,0.105,0.149,0.206;0.8,0.8))

Step 6: Defuzzifying and normalizing the type-2 fuzzy weights: Using Eq. (9), the defuzzified weights of the risk factors are shown in table 8.

Table 8. Defuzzified weights

	Defuzzified weights	**Normalized weights**
O	0.63	0.653
S	0.23	0.243
D	0.13	0.142

Phase 2. Prioritization of HRM risks through using Interval type-2 fuzzy TOPSIS technique.

The HRM risks are evaluated in state organizations according to the following steps after determining the weights of risk factors:

Step 1. Construct the decision matrix (Y_P): In this step, the TOPSIS questionnaire is developed and distributed among the experts based on the determined HRM risks and risk factors. This questionnaire uses the linguistic variables and type-2 fuzzy numbers according to table 9.

Table 9. Linguistic variables and type-2 fuzzy numbers

Linguistic variables	Interval type-2 fuzzy sets
Very Low (VL)	((0, 0, 0, 0.1; 1, 1), (0, 0, 0, 0.05; 0.9, 0.9))
Low (L)	((0, 0.1, 0.1, 0.3; 1, 1), (0.05, 0.1, 0.1, 0.2; 0.9, 0.9))
Medium Low (ML)	((0.1, 0.3, 0.3, 0.5; 1, 1), (0.2, 0.3, 0.3, 0.4; 0.9, 0.9))
Medium (M)	((0.3, 0.5, 0.5, 0.7; 1, 1), (0.4, 0.5, 0.5, 0.6; 0.9, 0.9))
Medium High (MH)	((0.5, 0.7, 0.7, 0.9; 1, 1), (0.6, 0.7, 0.7, 0.8; 0.9, 0.9))
High (H)	((0.7, 0.9, 0.9, 1; 1, 1), (0.8, 0.9, 0.9, 0.95; 0.9, 0.9))
Very High (VH)	((0.9, 1, 1, 1; 1, 1), (0.95, 1, 1, 1; 0.9, 0.9))

After collecting the results of experts' assessment in the forms of linguistic variables and converting them into type-2 fuzzy numbers, the matrix for aggregation of expert opinions on evaluation of HRM risks in each of the risk factors.

Table 10. Decision matrix

	O	S	D
A_1	((0.267,0.433,0.433,0.6;1,1),(0.35,0.433,0.433,0.517;0.9,0.9))	((0.7,0.9,0.9,1;1,1),(0.8,0.9,0.9,0.95;0.9,0.9))	((0.467,0.633,0.633,0.767;1,1),(0.55,0.633,0.633,0.7;0.9,0.9))
A_2	((0.267,0.433,0.433,0.633;1,1),(0.35,0.433,0.433,0.533;0.9,0.9))	((0.767,0.9,0.9,0.967;1,1),(0.833,0.9,0.9,0.933;0.9,0.9))	((0.333,0.5,0.5,0.667;1,1),(0.417,0.5,0.5,0.583;0.9,0.9))
A_3	((0.4,0.533,0.533,0.667;1,1),(0.467,0.533,0.533,0.6;0.9,0.9))	((0,0.1,0.1,0.3;1,1),(0.05,0.1,0.1,0.2;0.9,0.9))	((0,0.1,0.1,0.3;1,1),(0.05,0.1,0.1,0.2;0.9,0.9))
A_4	((0.7,0.867,0.867,0.967;1,1),(0.783,0.867,0.867,0.917;0.9,0.9))	((0.9,1,1,1;1,1),(0.95,1,1,1;0.9,0.9))	((0.2,0.367,0.367,0.567;1,1),(0.283,0.367,0.367,0.467;0.9,0.9))
A_5	((0.467,0.633,0.633,0.767;1,1),(0.55,0.633,0.633,0.7;0.9,0.9))	((0.833,0.967,0.967,1;1,1),(0.9,0.967,0.967,0.983;0.9,0.9))	((0.7,0.867,0.867,0.967;1,1),(0.783,0.867,0.867,0.917;0.9,0.9))
A_6	((0.233,0.367,0.367,0.533;1,1),(0.3,0.367,0.367,0.45;0.9,0.9))	((0.767,0.933,0.933,1;1,1),(0.85,0.933,0.933,0.967;0.9,0.9))	((0.567,0.733,0.733,0.867;1,1),(0.65,0.733,0.733,0.8;0.9,0.9))
A_7	((0.033,0.167,0.167,0.367;1,1),(0.1,0.167,0.167,0.267;0.9,0.9))	((0.833,0.967,0.967,1;1,1),(0.9,0.967,0.967,0.983;0.9,0.9))	((0.7,0.867,0.867,0.967;1,1),(0.783,0.867,0.867,0.917;0.9,0.9))
A_8	((0.533,0.667,0.667,0.767;1,1),(0.6,0.667,0.667,0.717;0.9,0.9))	((0.833,0.967,0.967,1;1,1),(0.9,0.967,0.967,0.983;0.9,0.9))	((0.567,0.733,0.733,0.867;1,1),(0.65,0.733,0.733,0.8;0.9,0.9))
A_9	((0.567,0.733,0.733,0.867;1,1),(0.65,0.733,0.733,0.8;0.9,0.9))	((0.9,1,1,1;1,1),(0.95,1,1,1;0.9,0.9))	((0.45,0.567,0.567,0.667;1,1),(0.517,0.567,0.567,0.617;0.9,0.9))
A_{10}	((0.2,0.367,0.367,0.567;1,1),(0.283,0.367,0.367,0.467;0.9,0.9))	((0.7,0.9,0.9,1;1,1),(0.8,0.9,0.9,0.95;0.9,0.9))	((0.333,0.467,0.467,0.6;1,1),(0.4,0.467,0.467,0.533;0.9,0.9))

A_{11}	((0.033,0.167,0.167,0.367;1,1),(0.1,0.167,0.167,0.267;0.9,0.9))	((0.9,1,1,1;1,1),(0.95,1,1,1;0.9,0.9))	((0.7,0.867,0.867,0.967;1,1),(0.783,0.867,0.867,0.917;0.9,0.9))
A_{12}	((0.3,0.4,0.4,0.533;1,1),(0.35,0.4,0.4,0.467;0.9,0.9))	((0.9,1,1,1;1,1),(0.95,1,1,1;0.9,0.9))	((0.567,0.767,0.767,0.9;1,1),(0.667,0.767,0.767,0.833;0.9,0.9))

Step 2. Explanation of weighted matrix ($\overline{W}$): In this step, the weighted matrix of HRM risk evaluation is formed based on the Eq. (15) and based on the determined weights for each risk factor through type-2 fuzzy AHP, and matrix for aggregation of expert opinions.

Table 11. Weighted Decision Matrix

Row	Criterion 1 (Weighted Values)	Criterion 2 (Weighted Values)	Criterion 3 (Weighted Values)
1	(0.124, 0.23, 0.325, 0.57; 1, 1), (0.157, 0.239, 0.324, 0.469; 0.8, 0.8)	(0.093, 0.165, 0.265, 0.382; 1, 1), (0.115, 0.172, 0.253, 0.343; 0.8, 0.8)	(0.039, 0.064, 0.101, 0.173; 1, 1), (0.047, 0.066, 0.095, 0.144; 0.8, 0.8)
2	(0.114, 0.23, 0.335, 0.602; 1, 1), (0.157, 0.239, 0.324, 0.485; 0.8, 0.8)	(0.102, 0.165, 0.265, 0.37; 1, 1), (0.12, 0.172, 0.253, 0.337; 0.8, 0.8)	(0.028, 0.051, 0.079, 0.15; 1, 1), (0.036, 0.052, 0.075, 0.12; 0.8, 0.8)
3	(0.17, 0.283, 0.413, 0.634; 1, 1), (0.209, 0.295, 0.399, 0.545; 0.8, 0.8)	(0, 0.018, 0.029, 0.115; 1, 1), (0.007, 0.019, 0.028, 0.072; 0.8, 0.8)	(0, 0.01, 0.016, 0.068; 1, 1), (0.004, 0.01, 0.015, 0.041; 0.8, 0.8)
4	(0.298, 0.46, 0.671, 0.919; 1, 1), (0.35, 0.479, 0.648, 0.833; 0.8, 0.8)	(0.119, 0.183, 0.294, 0.382; 1, 1), (0.137, 0.191, 0.282, 0.361; 0.8, 0.8)	(0.017, 0.037, 0.058, 0.128; 1, 1), (0.024, 0.038, 0.055, 0.096; 0.8, 0.8)
5	(0.199, 0.336, 0.49, 0.729; 1, 1), (0.246, 0.35, 0.473, 0.636; 0.8, 0.8)	(0.11, 0.177, 0.284, 0.382; 1, 1), (0.13, 0.185, 0.272, 0.355; 0.8, 0.8)	(0.058, 0.088, 0.138, 0.218; 1, 1), (0.068, 0.091, 0.129, 0.189; 0.8, 0.8)
6	(0.099, 0.195, 0.284, 0.507; 1, 1), (0.134, 0.203, 0.274, 0.409; 0.8, 0.8)	(0.102, 0.171, 0.274, 0.382; 1, 1), (0.123, 0.179, 0.263, 0.349; 0.8, 0.8)	(0.047, 0.075, 0.116, 0.195; 1, 1), (0.056, 0.077, 0.109, 0.165; 0.8, 0.8)
7	(0.014, 0.088, 0.129, 0.348; 1, 1), (0.045, 0.092, 0.125, 0.242; 0.8, 0.8)	(0.11, 0.177, 0.284, 0.382; 1, 1), (0.13, 0.185, 0.272, 0.355; 0.8, 0.8)	(0.058, 0.088, 0.138, 0.218; 1, 1), (0.068, 0.091, 0.129, 0.189; 0.8, 0.8)
8	(0.227, 0.354, 0.516, 0.729; 1, 1), (0.268, 0.368, 0.498, 0.651; 0.8, 0.8)	(0.11, 0.177, 0.284, 0.382; 1, 1), (0.13, 0.185, 0.272, 0.355; 0.8, 0.8)	(0.047, 0.075, 0.116, 0.195; 1, 1), (0.056, 0.077, 0.109, 0.165; 0.8, 0.8)
9	(0.241, 0.389, 0.567, 0.824; 1, 1), (0.291, 0.405, 0.548, 0.727; 0.8, 0.8)	(0.119, 0.183, 0.294, 0.382; 1, 1), (0.137, 0.191, 0.282, 0.361; 0.8, 0.8)	(0.038, 0.058, 0.09, 0.15; 1, 1), (0.045, 0.059, 0.085, 0.127; 0.8, 0.8)
10	(0.085, 0.195, 0.284, 0.538; 1, 1), (0.127, 0.203, 0.274, 0.424; 0.8, 0.8)	(0.093, 0.165, 0.265, 0.382; 1, 1), (0.115, 0.172, 0.253, 0.343; 0.8, 0.8)	(0.028, 0.047, 0.074, 0.135; 1, 1), (0.035, 0.049, 0.07, 0.11; 0.8, 0.8)
11	(0.014, 0.088, 0.129, 0.348; 1, 1), (0.045, 0.092, 0.125, 0.242; 0.8, 0.8)	(0.119, 0.183, 0.294, 0.382; 1, 1), (0.137, 0.191, 0.282, 0.361; 0.8, 0.8)	(0.058, 0.088, 0.138, 0.218; 1, 1), (0.068, 0.091, 0.129, 0.189; 0.8, 0.8)

Row	Criterion 1 (Weighted Values)	Criterion 2 (Weighted Values)	Criterion 3 (Weighted Values)
12	(0.128, 0.212, 0.31, 0.507; 1, 1), (0.157, 0.221, 0.299, 0.424; 0.8, 0.8)	(0.119, 0.183, 0.294, 0.382; 1, 1), (0.137, 0.191, 0.282, 0.361; 0.8, 0.8)	(0.047, 0.078, 0.122, 0.203; 1, 1), (0.058, 0.08, 0.114, 0.172; 0.8, 0.8)

Step 3: Rank Matrix: In this step, the ranks of all 12 HRM risks in three risk factors are determined based on the Eq. (16) and weighted matrix.

Table 12. Rank Matrix

Rank	O	S	D
A_1	5.216	4.808	4.077
A_2	5.229	4.812	3.979
A_3	5.593	3.752	3.684
A_4	6.815	4.942	3.881
A_5	5.953	4.897	4.250
A_6	4.981	4.852	4.152
A_7	4.243	4.897	4.250
A_8	6.080	4.897	4.152
A_9	6.328	4.942	4.028
A_{10}	4.979	4.808	3.953
A_{11}	4.243	4.942	4.250
A_{12}	5.108	4.942	4.175

Step 4. Determination of positive and negative ideals: Based on 10 and Eqs. (17) and (18), the negative and positive ideal values are described as follows:

Table 13. Positive and negative ideals

	O	S	D
V^+	6.835	4.952	4.450
V^-	4.143	3.752	3.674

Step 5: Based on the Eqs. (19) and (20), we can calculate the distance $d^+(x_j)$ between each alternative x_j and the ideal solution X^+ and we can calculate the distance $d^-(x_j)$ between each alternative x_j and the negative ideal solution X^-, respectively, where $1 \le j \le 3$, and then the relative degree of closeness is calculated according to Eq. (21) as shown in Table 14.

Table 14. Distance between HRM risks and negative and positive ideals

HRM Risk	Negative (NID)	Ideal Positive (PID)	Ideal Relative (RC)	Closeness Risk Severity
Weakness in employee retention	1.614	1.488	0.480	Moderate ( )
Poor ethics	1.615	1.477	0.470	Moderate ( )
Legislative limitations	1.797	1.350	0.429	Moderate ( )
Lack of justice	**0.370**	**2.841**	**0.885**	**Critical ( )**
Weakness in selection/recruitment	0.863	2.135	0.712	High ( )
Lack of senior management support	1.839	1.405	0.433	Moderate ( )
Weakness in employee training	**2.573**	**1.277**	**0.332**	**Low ( )**
Performance evaluation problems	0.743	2.215	0.749	High ( )
Employee health/well-being risk	0.535	2.426	0.819	Critical ( )
Reward problems	1.865	1.315	0.413	Moderate ( )
Financial problems	**2.573**	**1.317**	**0.339**	**Low ( )**
Lack of appropriate planning	1.709	1.551	0.476	Moderate ( )

4. Discussion and Conclusion

In today's rapidly shifting business landscape, organizations face unprecedented volatility, requiring agile responses to emerging human resource (HR) challenges. Scholarly investigations highlight how unaddressed HR risks can destabilize core operations—from project timelines and budgets to service quality and workforce productivity. Proactive identification of these threats enables organizations to mitigate losses while capitalizing on strategic opportunities, fostering long-term resilience. Drawing on empirical research and expert insights, this study examines twelve critical HR vulnerabilities prevalent in public-sector institutions, including talent retention gaps, ethical lapses, regulatory constraints, and systemic inequities. To address these issues, we propose a robust risk assessment framework integrating Failure Mode and Effects Analysis (FMEA) with advanced uncertainty modeling. This method refines traditional fuzzy logic approaches by incorporating multi-tiered weighting systems, offering greater precision in evaluating risk severity, detectability, and organizational impact. Preliminary testing identified four priority areas demanding intervention: nepotism, employee well-being deficiencies, flawed performance evaluations, and recruitment inefficiencies.Contemporary organizations operate in volatile conditions marked by continual disruption and instability (Pal et al., 2014). Researchers have progressively turned their attention to analyzing threats impacting HR practitioners. Early detection of these vulnerabilities allows enterprises to maximize advantages while minimizing drawbacks across essential operational aspects such as project schedules, financial outlays, service standards, labor efficiency, and departmental effectiveness (Ivančan & Lisjak, 2021). Structured risk evaluation helps institutions realize significant cost savings over extended periods while providing executives with sharper strategic understanding. This highlights the crucial nature of threat recognition for initiative success, as failure to acknowledge potential dangers - and their corresponding opportunities - might compromise corporate investments (Cervone, 2006). Our examination of academic literature, combined with specialist consultations and empirical studies across government agencies, uncovered twelve principal HR vulnerabilities: difficulties retaining talent, moral shortcomings, legal limitations, preferential treatment, deficient recruitment methods, inadequate leadership endorsement, poor training systems, unreliable appraisal mechanisms, occupational safety issues, remuneration challenges, fiscal restrictions, and ineffective foresight planning. To combat these obstacles, we suggest a novel assessment framework employing refined

FMEA techniques with sophisticated uncertainty modeling (Abdelgawad & Fayek, 2010). This enhanced approach extends Zadeh's pioneering concepts (1975) through more nuanced handling of ambiguous data via tiered participation scales. Where conventional fuzzy models deliver elementary uncertainty management, these upgraded versions provide superior precision when processing indeterminate scenarios (Mendel, 2007). Our technique implements this advanced reasoning within risk assessment protocols, initially applying weighted analysis (Kahraman et al., 2014) to gauge risk probability, impact, and identifiability, then utilizing prioritized sorting (Chen & Lee, 2010) for threat classification. Government sector trials revealed four predominant concerns: biased workplace practices (particularly cronyism), staff welfare considerations, defective evaluation processes, and talent acquisition flaws.

Workplace equity profoundly shapes employee behavior and productivity (Colarelli, 2013). When personnel perceive impartial treatment, they typically demonstrate enhanced output, favorable work perspectives, decreased anxiety, increased contentment, lasting dedication, confidence in leadership, and organizational loyalty (Pearce, 2015). Conversely, discriminatory conduct fosters workforce discontent, negative corporate perceptions, impaired wellbeing, inferior performance, occupational dissatisfaction, and psychological consequences including tension, absenteeism, and attrition. Worker welfare constitutes another vital consideration directly influencing job satisfaction. Employers must emphasize health protection measures, as negligence in this domain consistently undermines operational standards (Glendon et al., 2016). Performance appraisal weaknesses, frequently arising from inconsistent methodologies (Bitsch et al., 2006; Meyer et al., 2011), equally require executive focus. Recruitment complications often stem from divergences between institutional aims and employee expectations, creating perceived fulfillment deficits. Our methodology effectively addresses the inherent ambiguities in HR risk assessment by integrating advanced uncertainty modeling with traditional FMEA principles. Unlike conventional approaches that often struggle with subjective judgments and linguistic imprecision, our refined framework leverages type-2 fuzzy logic to capture nuanced expert inputs more accurately. The enhanced weighting system, powered by type-2 fuzzy AHP, eliminates the oversimplification common in traditional risk scoring by accounting for variability in expert opinions and contextual factors. This results in more precise and reliable risk evaluations that reflect real-world complexities. Furthermore, the upgraded classification mechanism through type-2 fuzzy TOPSIS provides a dynamic prioritization structure, allowing organizations to focus resources on the most critical vulnerabilities first. By incorporating second-order uncertainty modeling, the system reduces the risk of misclassification that often occurs with rigid, score-based FMEA methods. This targeted approach not only improves risk mitigation efficiency but also supports data-driven decision-making in HR policy development.

Practical applications in public sector organizations have demonstrated the framework's ability to uncover hidden risks—such as systemic biases in promotions or gaps in occupational health policies—that traditional methods might overlook. The adaptability of the system ensures relevance across diverse HR contexts, from talent retention crises to compliance failures, making it a robust tool for modern workforce risk management.

References

[1] Abdelgawad, M., & Fayek, A. R. (2010). Risk Management in the Construction Industry Using Combined Fuzzy FMEA and Fuzzy AHP. *Journal of Construction Engineering and Management*, *136*(9), 1028–1036. https://doi.org/10.1061/(asce)co.1943-7862.0000210

[2] Anwar, G., & Abdullah, N. N. (2021). The impact of Human resource management practice on Organizational performance. *International Journal of Engineering Business and Management*, *5*(1), 35–47. https://doi.org/10.22161/ijebm.5.1.4

[3] Berman, E. M., Bowman, J. S., West, J. P., & Van Wart, M. R. (2019). *Human resource management in public service: Paradoxes, processes, and problems*. CQ Press.

[4] Bessis, J. (2002). Risk Management in Banking, John Willey & Sons. *Inc., New York*.

[5] Bitsch, V., Kassa, G. A., Harsh, S. B., & Mugera, A. W. (2006). Human resource management risks: sources and control strategies based on dairy farmer focus groups. *Journal of Agricultural and Applied Economics*, *38*(1), 123–136.

[6] Bowles, J. B., & Peláez, C. E. (1995). Fuzzy logic prioritization of failures in a system failure mode, effects and criticality analysis. *Reliability Engineering & System Safety*, *50*(2), 203–213.

[7] Cervone, H. F. (2006). Project risk management. *OCLC Systems & Services: International Digital Library Perspectives*.

[8] Chance, D. M., & Brooks, R. (2015). *Introduction to derivatives and risk management*. Cengage Learning.

[9] Chen, L.-H., & Ko, W.-C. (2009). Fuzzy linear programming models for new product design using QFD with FMEA. *Applied Mathematical Modelling*, *33*(2), 633–647.

[10] Chen, S.-M., & Lee, L.-W. (2010). Fuzzy multiple attributes group decision-making based on the interval

type-2 TOPSIS method. *Expert Systems with Applications*, *37*(4), 2790–2798. https://doi.org/10.1016/j.eswa.2009.09.012

[11] Chewning, L. V., Lai, C.-H., & Doerfel, M. L. (2013). Organizational Resilience and Using Information and Communication Technologies to Rebuild Communication Structures. *Management Communication Quarterly*, *27*(2), 237–263. https://doi.org/10.1177/0893318912465815

[12] Chou, Y., Yen, H.-Y., Van Thac Dang, & Sun, C. (2019). Assessing the Human Resource in Science and Technology for Asian Countries: Application of Fuzzy AHP and Fuzzy TOPSIS. *Symmetry*, *11*(2), 251–251. https://doi.org/10.3390/sym11020251

[13] Coupland, S., & John, R. (2008). Type-2 Fuzzy Logic and The Modeling of Uncertainty, Fuzzy Sets and Their Extensions: Representation, Aggregation and Models. *Springer Berlin / Heidelberg*, *220*, 3–22.

[14] Dağsuyu, C., Göçmen, E., Narlı, M., & Kokangül, A. (2016). Classical and fuzzy FMEA risk analysis in a sterilization unit. *Computers & Industrial Engineering*, *101*, 286–294. https://doi.org/10.1016/j.cie.2016.09.015

[15] Garcia, P. A. A., & Schirru, R. (2005). A fuzzy data envelopment analysis approach for FMEA. *Progress in Nuclear Energy*, *46*(3–4), 359–373.

[16] Glendon, A. I., Clarke, S., & McKenna, E. (2016). *Human safety and risk management*. Crc Press.

[17] Hotho, J., Minbaeva, D., Muratbekova-Touron, M., & Rabbiosi, L. (2020). Coping with favoritism in recruitment and selection: a communal perspective. *Journal of Business Ethics*, *165*(4), 659–679.

[18] Huber, C., & Scheytt, T. (2013). The dispositif of risk management: Reconstructing risk management after the financial crisis. *Management Accounting Research*, *24*(2), 88–99.

[19] Ivančan, J., & Lisjak, D. (2021). New FMEA Risks Ranking Approach Utilizing Four Fuzzy Logic Systems. Machines, 9(11), 292–292. https://doi.org/10.3390/machines9110292

[20] Kahraman, C., Öztayşi, B., Uçal Sarı, İ., & Turanoğlu, E. (2014). Fuzzy analytic hierarchy process with interval type-2 fuzzy sets. *Knowledge-Based Systems*, *59*, 48–57. https://doi.org/10.1016/j.knosys.2014.02.001

[21] Kahraman, C., ßar, B., ßi, Ö., Sarı, I. U., & Turanog ˘lu, E. (2014). Fuzzy analytic hierarchy process with interval type-2 fuzzy sets. *Knowledge-Based Systems*, *59*, 48–57. https://doi.org/10.1016/j.knosys.2014.02.001

[22] Karnik, N. N., Mendel, J. M., & Qilian, L. (1999). Type- 2 Fuzzy Logic Systems. *IEEE Transactions on Fuzzy Systems*, *7*, 643–658.

[23] Kumar, K. A., & Raja, R. V. (2014). Impact of poor recruitment, selection and training over the staff turnover in a bpo. *ZENITH International Journal of Multidisciplinary Research*, *4*(7), 155–170.

[24] Kutlu, A. C., & Ekmekçioğlu, M. (2012). Fuzzy failure modes and effects analysis by using fuzzy TOPSIS-based fuzzy AHP. *Expert Systems with Applications*, *39*(1), 61–67.

[25] Li, J. J., Kim, W. G., & Zhao, X. R. (2017). Multilevel model of management support and casino employee turnover intention. *Tourism Management*, *59*, 193–204.

[26] Mendel, J. M. (2007). Type-2 Fuzzy Sets and Systems: an Overview. *Computational Intelligence Magazine, IEEE*, *2*, 20–29.

[27] Mendonça, D., & Wallace, W. A. (2015). Factors underlying organizational resilience: The case of electric power restoration in New York City after 11 September 2001. *Reliability Engineering & System Safety*, *141*, 83–91. https://doi.org/https://doi.org/10.1016/j.ress.2015.03.017

[28] Mohiuddin, M., Hosseini, E., Faradonbeh, S. B., & Sabokro, M. (2022). Achieving Human Resource Management Sustainability in Universities. *International Journal of Environmental Research and Public Health*, *19*(2), 928–928. https://doi.org/10.3390/ijerph19020928

[29] Meyer, M., Roodt, G., & Robbins, M. (2011). Human resources risk management: governing people risks for improved performance: opinion paper. *SA Journal of Human Resource Management*, *9*(1), 1–12.

[30] Nyaaba Joseph, H. (2014). *The effect of recruitment and selection practices on work ethics; A case study of the Ghana Police Service*.

[31] Oborilová, I., Myšková, R., & Melichar, V. (2015). Risks Associated with the Human Resources Management in Transport Companies. *Procedia Economics and Finance*, *34*, 352–359. https://doi.org/https://doi.org/10.1016/S2212-5671(15)01640-8

[32] Pal, R., Torstensson, H., & Mattila, H. (2014). Antecedents of organizational resilience in economic crises—an empirical study of Swedish textile and clothing SMEs. *International Journal of Production Economics*, *147*, 410–428. https://doi.org/10.1016/j.ijpe.2013.02.031

[33] Pearce, J. L. (2015). Cronyism and nepotism are bad for everyone: The research evidence. *Industrial and Organizational Psychology*, *8*(1), 41–44.

[34] Rafie, M., & Samimi Namin, F. (2015). Prediction of subsidence risk by FMEA using artificial neural

network and fuzzy inference system. *International Journal of Mining Science and Technology*, *25*(4), 655–663. https://doi.org/10.1016/j.ijmst.2015.05.021
[35] Storey, J. (2014). *New Perspectives on Human Resource Management (Routledge Revivals)*. Routledge.
[36] Tooranloo, H. S., & sadat Ayatollah, A. (2016). A model for failure mode and effects analysis based on intuitionistic fuzzy approach. *Applied Soft Computing*, *49*, 238–247.
[37] Tung, R. L. (2016). New perspectives on human resource management in a global context. *Journal of World Business*, *51*(1), 142–152.
[38] Ukandu, N. E., & Ukpere, W. I. (2013). Effects of poor training and development on the work performance of the fast food employees in Cape Town. *Mediterranean Journal of Social Sciences*, *4*(14), 571.