

An AHP-Modified TOPSIS and Pareto Model for Employee Turnover Intention Analysis

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ABSTRACT

Employee turnover intention (TOI) is a significant challenge that affects an organization financially, particularly in the context of Indonesian academic sector, where turnover rate is notably high. This study uses a primary Indonesian academic dataset and proposes a novel framework for Indonesian academic turnover intention (TOI) encompassing Analytic hierarchy process (AHP), Modified TOPSIS combined with Pareto principle and compares the proposed framework with existing framework of entropy-based weighted method, traditional TOPSIS and interval scaling for categorizing academic employees according to productivity. The AHP procedure encompasses hybrid logarithmic linear normalization integrating linear as well as logarithmic normalization, consequently ensuring consistency and robustness for categorization of TOI. The proposed framework integrates Euclidean, Manhattan, Chebyshev distance for resolving the issues of traditional TOPSIS for ranking alternatives. The modified TOPSIS incorporates Information Gain, Recursive feature elimination (RFE) and Select K-best for finding Indonesian academic TOI. Random forest was implemented as the baseline classifier model for both the proposed and existing scheme. Experimental results revealed that proposed approach achieved higher predictive accuracy in contrast to the existing approach for categorizing employees into enthusiastic, behavioral and distressed. Therefore, this study establishes a robust approach for employee categorization outperforming the existing approach.

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1. INTRODUCTION

Employee turnover is a challenging issue in organizational and business management. Whenever an employee leaves an organization, the organization faces significant losses [9]. So, it is imperative to prevent employee turnover mitigating the negative impacts within an organization. Thus, the need for finding out employee turnover intention is of significant importance because employee turnover intention can actually be helpful to find out the actual turnover within an organization[24]. In Indonesia, the turnover of employees is significant leading to an astonishing rate of 15.8%[11] and it is more pronounced in academic field of Indonesia. For instance, numerous studies revealed the fact that the turnover intention of Indonesian lecturer is pretty high, with one province in Indonesian private higher education having reached academic employee turnover rate of 62% [20], which prompts the need to find out the academic turnover intention in Indonesian private higher education institutes, consequently targeting to reduce the academic TOI in Indonesian private academic field.

Failure to address Employee turnover intention (TOI) properly will lead to actual turnover among

academic employees, leading to financial losses. Thus, the need for finding out TOI among Indonesian academicians in a nuanced way carries great significance.

Academic employee turnover intention has been categorized based on different categories. For instance, academic employees have been categorized according to turnover intention based on transfer (switching to another educational organization) and quit (Changing to another job other than academic)[22]. Moreover, academic employees have been categorized into spin-off (commercialize scientific finding while maintaining relationship with academic institution), startup (creating new entrepreneurial business), leaving academia, and changing institutions [3]. Although employee categorization according to turnover has been accomplished based on productivity [14], the categorization of academic employee TOI based on productivity has been under-explored, specifically in the context of Indonesian academic sectors where academic turnover is significantly high. If academic employees are categorized based on TOI and productivity, this can help find out the least productive academic employees in advance and take necessary action to resolve the issues for the least productive employees.

The objective of this research is to design an AHP-Modified TOPSIS paired with Pareto principle to categorize employees according to TOI based on productivity. The impact of extreme values has been reduced with maintenance of ranking for the features in the AHP procedure by incorporating hybrid logarithmic linear normalization. The TOI of employees are categorized into enthusiastic, behavioral and distressed where enthusiastic employees are most productive, behavioral are moderate productive and distressed employees are least productive. TOPSIS is an MCDM method that is well known for its simplicity decision making capabilities and computational efficiency [5]. However, each of the distance metrics used in TOPSIS, such as Chebyshev, Euclidean distance and Manhattan distance suffers from few issues which can impact the overall decision making capability of TOPSIS. This article aims to integrate different distance metrics in TOPSIS to provide an accurate approach for decision making, in this case, the accurate detection of employee TOI based on productivity.

In spite of turnover intention being widely studied in MCDM and machine learning, very few works focus on the categorization of employees according to turnover intention based on productivity. Furthermore, traditional TOPSIS suffers from distance metrics limitations and sensitivity issues to outliers.

The significance of this study lies in the accurate detection of Indonesian private academic employee categorization according to TOI. The proposed approach would be compared to entropy-based weighted approach, TOPSIS and interval scaling approach for detecting TOI and it is hypothesized that the proposed approach would outperform the entropy-based weighted approach because of incorporating subjective weights by decision makers for pairwise comparisons in AHP [8] compared to entropy-based weighted method minimizing subjective judgements leading to the potential of elimination of criteria when all alternatives share same criteria value [25]. In order to ensure the reliability of subjective judgement, five HR academic experts with an average expertise of over a decade in Indonesian higher education HR evaluation provided their subjective judgement. The selection procedure of experts was in line with the present labor market of Indonesian lecturers where the turnover was very high [26], in fact in one Indonesian province the turnover rate reached an astonishing rate of 62%. Moreover, the consistency ratio was calculated to ensure the feasibility of expert responses. This ensures that assigned weights reflected the real Indonesian workforce priorities while increasing the contextual validity.

Furthermore, AHP confirms the consistency of expert responses in decision matrix [27] while Shannon's entropy-based weighted method can result in inconsistency for outlier data [23]. The contribution of this research is an application-oriented refinement of ensemble approach for academic turnover intention analysis. Mainly, the study contributes to academic turnover intention analysis in four ways: 1) Introducing hybrid logarithmic-linear normalization while preserving expert's preference ordering for reducing influence of extreme pairwise judgments in AHP 2) Defining a modified TOPSIS integrating Euclidean, Manhattan, and Chebyshev components within a logarithmic transformation, thereby balancing sensitivity and robustness, consequently yielding high performance metrics 3) Incorporation of AHP-modified TOPSIS to rank employees according to turnover intention and using Pareto based 20-30-50 segmentation to categorize employees according to productivity. 4) Overall, providing a tradeoff between time and performance between proposed and existing approach.

The rest of the paper is organized as follows. Section 2 discusses the relevant works focusing on employee turnover intention and categorization methodologies. The proposed framework is described in detail in section 3, which describes the AHP-Modified TOPSIS approach integrated with the Pareto principle. Section 4 elaborates on the evaluation methodology, including performance metrics. Section 5 depicts experimental results and comparative findings between the proposed and existing schemes incorporating entropy, traditional

TOPSIS and weighted sum approach. Finally, section 6 concludes with future directions of the work.

2. RELATED WORKS

TOI is a challenging issue for organizations. Although employee turnover has been extensively explored via numerous machine learning classifier models and frameworks, the integration of predictive analytics with multi-criteria decision making models and Pareto principle for TOI is an under-explored sector in business analytics. In this section of related works, the summarization of machine learning models, Pareto principle, entropy-based and MCDM methods associated to turnover has been explored briefly. Park et al [21] implemented ERG theory integrated with KNN, LR and XGB machine learning models for predicting TOI. Job security and job person fit was found to be the most significant factors while workload was pshown to have lesser impact on TOI for new graduates. Zivkovic et al [30] demonstrated the implementation of decision trees for employee TOI indicating the limited research on this issue. Data gathered from 15 Croatian organizations including agriculture, tourism and educational sector revealed that personal growth, affective commitment and salary satisfaction were the predictive factors for TOI. Several decision tree algorithms were implemented and RF had the highest recall showing the predictive power of RF. Lazzari et al [18] surveyed 18,322 employees within 30 European countries for Global Employee Engagement Index (GEEI) survey and assessed motivation, employer ship, sustainable employ ability as key determinants for TOI using machine learning models such as LIGHTGBM, LR. Structural causal model demonstrated that motivation was linked to TOI. Inventories have been classified into A,B and C classes using Pareto principle for inventory selection where class A is the most critical items that should be focused and class B and C are less significant items. This study also signifies the advantage of using machine learning classifiers for inventory selection and classification[17]. Furthermore, the integration of ML, MCDM and multi-attribute inventories have been categorized into distinct classes of 3 which is known A,B, C classes represents 20%, 30% and 50% of the total distribution[16]. learning classifiers for inventory selection and classification. In addition, Pareto principle has been applied for virtual classrooms in online university communities where it was revealed that 20% of the students were most interactive in forums for discussion, demonstrating the importance of Pareto principle[26]. Similarly, Pareto principle was applied in Turkish geothermal district heating system to recognize avoidable and unavoidable exergy destruction[2]. entropy-based weighted method has been used in order to find out the weights of factors to be incorporated into TOPSIS [14] for ranking employees according to turnover. Afterwards, an interval scaled method was used to categorize employees into three categories according to productivity. Furthermore, a combined approach using AHP, TOPSIS MCDM methods and ML algorithms with pareto principle have been implemented for employee turnover prediction [10]. Brazilian government electrical sectors used Analytic Hierarchy process and TOPSIS-2N hybrid model to find out the weighted importance of risk factors and ranked the electrical sector datasets based on the re- spective risk scores [1]. Like- wise, AHP-TOPSIS integration was used in four Colombian logistics companies for ranking based on their performance [15]. The traditional TOPSIS method uses different distance metrics to calculate the distance from ideal solution. For example, Euclidean distance, Chebyshev distance and Manhattan distance have been used in TOPSIS for measuring the distances. Each of these distance metrics have their pros and cons. Euclidean distance is well known for its ability for efficient geometric interpretation and ranking of multi-attribute decision-making issues[28], but it suffers from biasness of large range input value. On the other hand, Manhattan distance is unbiased with larger values as Euclidean distance. Lastly, Chebyshev distance is good at providing faster computation [29]. Euclidean distance is prone to larger variations where smaller changes has effect on the ranking of the alternatives, Manhattan distance smooths out outlier impact. On the contrary, Chebyshev distance takes the most significant differences across one factor, but is unable to capture subtle differences of rankings. The summary of the related work has been shown in the table below. It can be clearly visible from the table that there has been lack of exploration for dealing with the categorization of employee TOI according to productivity. Moreover, the use of distance metrics yields issues in TOPSIS which is yet to be resolved. This research aims to integrate three distance metrics to resolve the issues of traditional TOPSIS and hypothesizes that the use of modified TOPSIS and Pareto principle can have a better performance metrics for TOI categorization in contrast to existing entropy-based weighted method.

Table 1. Related works of AHP-TOPSIS, Pareto principle, and employee turnover intention

Author(s)	Dataset	Model/Approach	Focus Area	Key Findings
Park, J. et al.	Data collected from Korea Employment Info Service (2019 GOMS)	Implementation of ERG theory; KNN, LR, XGB classifier models	TOI among new graduates	Job security and job-person fit were significant factors, while workload showed lesser impact on TOI.
Živković, A. et al.	Data from 15 Croatian organizations across agriculture, tourism, and education	Decision Trees	Finding out TOI using organizational factors	Key predictors of TOI were personal growth, affective commitment, and satisfaction with salary.
Lazzari, M. et al.	18,322 instances from Global Employee Engagement Index (GEEI)	LightGBM, SCM	Find out the key causal drivers for TOI in European countries	Strong association found between motivation, employership, and TOI.
Khanorkar, Y. et al.	Annual usage value (ADU), lead time, and unit cost dataset	Pareto principle, Hadi-Vencheh MCDM model, K-means clustering method	Inventory classification	Classified inventories into class A, B, and C based on Pareto principle. ML manages large-scale inventory datasets efficiently.
Kartal, H. et al.	708 inventory items	MCDM methods (AHP, VIKOR, SAW) and ML models (Naive Bayes, ANN, SVM, Bayesian Network)	Efficient inventory classification for large datasets	SVM outperformed other models across frameworks of different MCDM methods for ABC analysis.
Serradell-Lopez, E. et al.	184 participants from Open University in Catalonia	Educational data mining approach	Academic outcomes in virtual classrooms	Pareto principle demonstrated that 20% of participants were engaged in most activities, dominating virtual communication.
Arslan, O. et al.	Simav GDHS from Turkey	Exergy analysis using advanced mechanism and Pareto principle	Detection of energy efficiency in district heating systems	Around 20% of exergy destruction was identified, which could be avoided.
Jain, N. et al.	Kaggle dataset (14,999 instances)	Entropy-based weighted method-TOPSIS, Pareto principle	Categorization of employees according to turnover	Employees categorized into three groups (enthusiastic, behavioral, distressed); key TOI factors identified for each group.
Chowdhury, S. J. et al.	Kaggle dataset	AHP-TOPSIS-Pareto principle, ML models	Employee churn prediction to reduce organizational cost	Random forest achieved the highest prediction accuracy when combined with MCDM methods.
Araújo, I. P. et al.	Electricity datasets from 44 Brazilian Open Data Portal	Hybrid AHP-TOPSIS-2N	Identifying key critical factors of electrical sectors and ranking sectors	Negative feedback and resource availability were impactful; datasets ranked based on rank scores.
Jiménez-Delgado, G. et al.	Data collected from logistics companies through surveys	Combined AHP-TOPSIS approach	Evaluating innovation processes in logistics and integrating management systems	Introduced a combined AHP-TOPSIS approach for evaluation integrating environmental, quality, and safety management systems.
Yin, H. et al.	Simulated dataset	Relative Euclidean distance with optimistic and pessimistic distance	Enhancement of traditional TOPSIS method	Optimistic distance feasible when choices are close to ideal solutions; pessimistic distance suitable for anti-ideal solutions.
Yulianti, L. P. et al.	10 benchmark UCI ML datasets	Clustering-based ensemble method using four distance metrics (Euclidean, Manhattan, Chebyshev, Canberra)	Impact of different distance metrics on clustering in ensemble learning	Chebyshev distance was best for diversity and purity for half of the datasets.

2.1. Data Collection

This dataset on employee turnover intention was collected via a detailed questionnaire distributed to 930 academicians at Indonesian private universities, with 527 voluntary responses. The dataset is available at <https://data.mendeley.com/datasets/m7fprjt84z/1>.

Table 2. Demographic summary for the primary dataset

Demographic Attribute	Category	Frequency	Percentage (%)
Gender	Male	222	42.08
	Female	305	57.92
Age Group	18–25 years	15	2.84
	26–35 years	283	53.69
	36–45 years	120	22.78
	46–55 years	84	15.94
	>56 years	25	4.74
Work Tenure	Less than 2 years	112	21.26
	3–5 years	166	31.49
	More than 5 years	249	47.25
Educational Qualification	Bachelor's degree	144	27.31
	Master's degree	273	51.80
	Doctorate/PhD	110	20.89
Job Position	Lecturer	258	48.96
	Senior Lecturer	147	27.90
	Assistant Professor	62	11.77
	Professor	38	7.21
	Associate Professor	22	4.17

3. METHODOLOGY

This section highlights details on the proposed framework and existing frameworks designed for addressing employee categorization according to turnover intention (TOI). The key stages of both the proposed and existing frameworks comprise input data, the feature selection process, output, and the categorization of

3.1. Proposed Framework

- **Input Data:** Proposed framework uses employee turnover features as input data.
- **Feature Selection Process:** A modified TOPSIS integrated with Information Gain, Recursive Feature Elimination (RFE), and Select K-best feature selection methods to find significant features of employee TOI.
- **Output:** Identify important selected features for employee TOI.
- **Categorization:** Implement AHP-Modified TOPSIS for ranking employees according to turnover intention and categorize employees into three categories using the De-Pareto principle.

3.2. Existing Framework

- **Input Data:** Set of Employee TOI features.
- **Feature Selection Process:** A permutation-based feature selection method by permuting feature values randomly to assess the importance of employee TOI.
- **Output:** Identify important selected features for employee TOI.
- **Categorization:** Implement an Entropy-based weighted method integrated with TOPSIS for ranking employees according to turnover intention and categorizing employees into three predefined categories.

3.3. Employee Categorization

The employee categorization has been done by categorizing employees according to productivity into three categories:

- **Enthusiastic:** Most productive employees.
- **Behavioral:** Employees with average productivity.

- **Distressed:** Least productive employees.

The workflow of proposed and existing scheme is given as below :

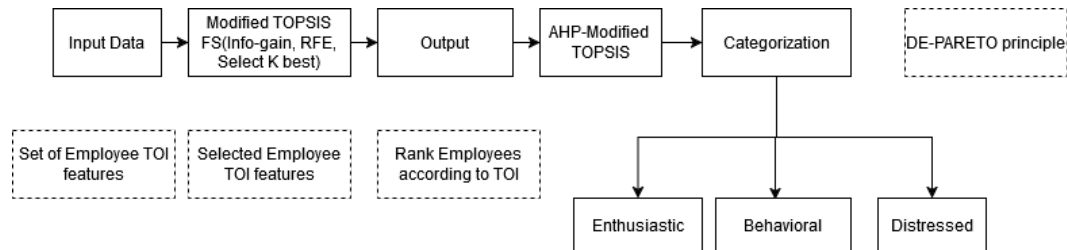


Figure 1. Proposed scheme using AHP-Modified TOPSIS and Pareto principle for employee categorization

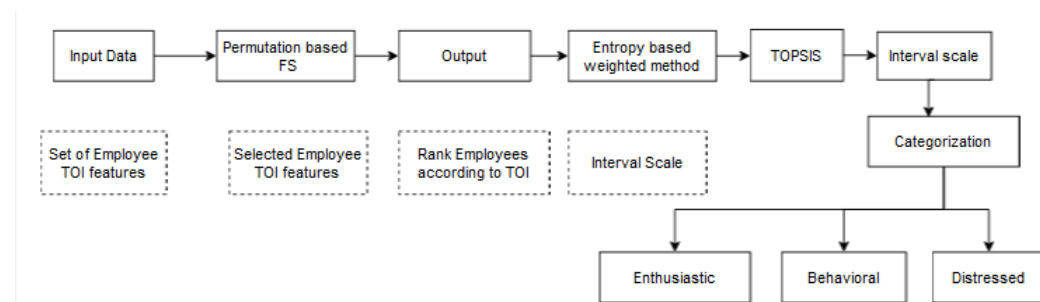


Figure 2. Existing scheme using entropy-based weighted method, TOPSIS and interval scale for employee categorization

In the subsequent sections below, Modified TOPSIS used for interrogation of feature selection and permutation based feature selection has been described briefly. Proposed scheme using Analytic hierarchy process (AHP) integrated with modified TOPSIS and De-parteo principle has been discussed for employee categorization. Next , the existing scheme utilizing entropy-based feature selection , traditional TOPSIS and Interval scale for employee categorization has been discussed herewith briefly.

3.4. Modified TOPSIS Feature Selection

Modified TOPSIS has been incorporated to identify and rank significant features.

- **Input:** A set of features for employee Turnover Intention (TOI).
- **Process:** Assign equal weights of 0.33 to each of the feature selection methods to compute the feature scores for each criterion using these weights.
- **Output:** Apply the Modified TOPSIS method to rank the features and select the top 10 best features for implementation.

3.5. Permutation-based Feature Selection Method

- **Input Data:** Set of features related to employee TOI, trained predictive model, baseline performance metrics for each model.
- **Process:** The model is tested on the dataset to establish a baseline performance score. Each feature is then shuffled, and the model is re-evaluated to measure the performance drop. The feature causing the largest drop is identified as the most important.
- **Output:** Top 10 features with the most performance drop has been identified as influential for making prediction.

Table 3. Feature Ranking Based on Information Gain, Select K Best, RFE Importance, and Modified TOPSIS Score

Rank	Feature	Info Gain	Select K Best Score	RFE Importance	Modified Score	TOPSIS
1	Work is meaning- ful	0.258827	302.967663	1	0.742164	
2	Kinship	0.214318	283.510830	1	0.742164	
3	Family supports	0.264581	338.326726	1	0.735460	
4	Satisfied with ca- reer and opportu- nity	0.289202	322.475929	1	0.731301	
5	Mentally well and do not have anxiety	0.299575	364.942572	1	0.723457	
6	Satisfied with work- life balance	0.302290	411.138744	1	0.715387	
7	Satisfied com- pensa- tion	0.317003	417.127252	1	0.711982	
8	Satisfied with job pro- fession	0.311528	471.553455	1	0.703404	
9	Working hour	0.180598	6.611628	1	0.687354	
10	Satisfaction with workload	0.363767	613.847322	1	0.674431	

Table 4. Permutation-based Top 10 Features

SL.	Feature
1	Satisfied compensation
2	Satisfaction with workload
3	Satisfied with job profession
4	Working hour
5	Work tenure
6	Gender
7	Education
8	Kinship
9	Job position
10	Mentally well and do not have anxiety

3.6. Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process is composed of the following steps:

Step 1: Pairwise Comparison Matrix

A pairwise comparison matrix is constructed using features with preference levels provided by experts.

Table 5. The pairwise matrix is represented as follows:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1k} \\ p_{21} & p_{22} & \cdots & p_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ p_{k1} & p_{k2} & \cdots & p_{kk} \end{bmatrix} \quad (1)$$

Table 5. Expert Preference Level

Value	Preference Level
1	No difference in liking
3	Moderate liking
5	Strong liking
7	Pronounced liking
9	Intense liking
2,4,6,8	Intermediate liking

Step 2: Normalized Decision Matrix

Normalization method is an important process of final decision making for decision makers since it has significant impact on the final outcome [4]. In order to produce robust results, multi-criteria decision making methods have frequently combined multiple normalization techniques [12]. With a view of doing so, hybrid logarithmic linear normalization has been used where:

$$N'_{ab} = \frac{\log(1 + P_{ab})}{\sum_{a=1}^k \log(1 + P_{ab})} \times \frac{P_{ab}}{\sum_{a=1}^k P_{ab}} \quad (2)$$

Where the first term is composed of logarithmic normalization and second term is the linear normalization. The above formula avoids the inconsistencies provided for logarithmic transformation by avoiding a value of zero, as well as preserving the ranking while reducing influence of extreme values. Normalized matrix for the first row:

$$Work\ is\ meaningful = \frac{1}{55} = 0.0182, \ Kinship = \frac{0.5}{45.5} = 0.0110, \ Family\ supports = \frac{0.333}{37} = 0.0090$$

Step 3: Geometric Mean and Consistency Ratio

The consistency ratio (CR) is calculated as follows:

$$\lambda_{\max} \approx 10.547, \ CI = \frac{\lambda_{\max} - n}{n - 1} \quad (3)$$

$$CI = \frac{10.547 - 10}{10 - 1} \approx 0.0607$$

$$CR = \frac{CI}{RI} \quad (4)$$

$$CR = \frac{0.0607}{1.49} \approx 0.0408$$

Since $CR < 0.1$, the subjective judgments are acceptable.

Step 4: Weighted Criteria

The final weights for each criterion are shown in Table 6.

Table 6. Weighted Criteria Using AHP

Criteria/Feature	Weight
Work is meaningful	0.0152
Kinship	0.0203
Family support	0.0284
Satisfied with career and opportunity	0.0401
Mentally well and no anxiety	0.0564
Satisfied with work-life balance	0.0788
Satisfied compensation	0.1094
Satisfied with job profession	0.1515
Working hour	0.2099
Workload satisfaction	0.2900

3.7. Modified TOPSIS Method

- **S1:** Incorporate the weights from AHP into the TOP 10 selected features or criteria.
- **S2:** Construct a decision matrix M with the TOP 10 features and the alternatives (records), where:

$$K = \text{number of records}, \ N = \text{number of features}.$$

$$M = \begin{bmatrix} M_{11} & M_{12} & M_{13} & \cdots \\ M_{21} & M_{22} & M_{23} & \cdots \\ \vdots & \vdots & \vdots & \ddots \\ M_{K1} & M_{K2} & M_{KN} & \end{bmatrix} \quad (5)$$

S5: Measurement of Positive and Negative Ideal Solutions Positive and negative ideal solutions are measured based on the formalization below:

- **Positive Ideal Solution (PIS):** Takes higher values for benefit criteria and lower values for cost criteria.

$$v_j^+ = \begin{cases} \max(v_{ij}), & \text{if criterion is beneficial} \\ \min(v_{ij}), & \text{if criterion is a cost} \end{cases} \quad (6)$$

- **Negative Ideal Solution (NIS):** Takes lower values for benefit criteria and higher values for cost criteria.

$$v_j^- = \begin{cases} \min(v_{ij}), & \text{if criterion is beneficial} \\ \max(v_{ij}), & \text{if criterion is a cost} \end{cases} \quad (7)$$

S4: Measure the closeness to the ideal solution by integrating log transformation with three distance metrics.

$$D_i^+ = \log \left(1 + \frac{\sum (X - A^+)^2}{SD} \right) + \log \left(1 + \frac{\sum |X - A^+|}{SD} \right) + \log \left(1 + \frac{\sum \max(X - A^+)}{SD} \right) \quad (8)$$

$$D_i^- = \log \left(1 + \frac{\sum (X - A^-)^2}{SD} \right) + \log \left(1 + \frac{\sum |X - A^-|}{SD} \right) + \log \left(1 + \frac{\sum \max(X - A^-)}{SD} \right) \quad (9)$$

In the traditional TOPSIS, the relative closeness coefficient is computed as $C_i = \frac{S_i^-}{S_i^+ + S_i^-}$. In this study, the formulation is enhanced by integrating logarithmic transformation with three distance metrics simultaneously – Euclidean, Manhattan, and Chebyshev distances to reduce scaling sensitivity and suppress outlier influence.

MRCC = $0.5 * (PC + OC)$ where PC = proximity closeness = $1/(D_i^+ + D_i^-)$, OC = opposition proximity closeness = $1/(1 + D_i^-)$.

Algorithm 1: AHP–Modified TOPSIS–Pareto Principle for TOI Classification

1. Employee dataset $\rightarrow X$, n = number of employees and m = number of criteria
2. Apply Information Gain + RFE + Select K-Best $\rightarrow$ Get features for TOI
3. Construct pairwise matrix $\rightarrow$ AHP weights w_j from the matrix
4. Using hybrid log–linearity for Normalizing decision matrix
5. Compute weighted normalized matrix $V_{ij} = w_j * x_{ij}$
6. Compute the positive/negative ideal solutions
7. Calculate three distances D_i^E, D_i^M, D_i^C , where D_i^E = Euclidean distance, D_i^M = Manhattan distance, D_i^C = Chebyshev distance
8. Aggregate equations (8)–(9) to compute Modified Relative Closeness Coefficient (MRCC) in equation (10). PC is used to find out the closeness to ideal solution whereas OC has been proposed as D_i^- decreases, the value is closest to ideal while furthest from negative ideal solution.
9. Rank employees based on closeness to ideal solution C_i and categorize employees using De-Pareto principle

Output: {Enthusiastic, Behavioral, Distressed group labels}

3.8. De-Pareto Principle

While implementing, employees are first sorted in descending order based on their Modified TOPSIS score S_i . Afterwards, the De-Pareto principle is applied in terms of fixed proportions: top 20% employees were labeled as the “enthusiastic” group (Most productive), the next 30% employees as the “behavioral” group (moderate productive), and the remaining employees as the “distressed” group (least productive). Thus, while the pareto principle 20-30-50 is implemented in fixed threshold, the categorization and group membership of employees was accomplished through empirical sorting of the employees.

3.9. Employee Turnover Intention with AHP-Modified TOPSIS and De-Pareto Principle

Table 7. Employee turnover intention ranking based on AHP-Modified TOPSIS and De-Pareto principle.

Employee	S_i	Rank
Emp1	0.747371712	9
Emp2	0.747773338	7
Emp3	0.748904906	3
Emp4	0.747747974	8
Emp5	0.74803417	5
Emp6	0.749636387	2
Emp7	0.74782191	6
Emp8	0.749644504	1
Emp9	0.748880272	4
Emp10	0.74652073	10

3.10. Entropy-Based Weighted Method

The detailed procedure for finding out the entropy-based weights for each criterion is given below:

S1: A decision matrix is constructed as below:

- n = academic employee number,
- m = criteria number.

The decision matrix is represented as:

$$D = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1c} \\ d_{21} & d_{22} & \cdots & d_{2c} \\ \vdots & \vdots & \ddots & \vdots \\ d_{n1} & d_{n2} & \cdots & d_{nm} \end{bmatrix} \quad (11)$$

Table 8. Vector Normalization Matrix

Feature Name	Satisfied Compensation	Satisfaction with Work-load	Satisfied with Job Profession	Working Hour	Work Tenure	Gender	Education	Good Relationship with Peers	Job Position	Mentally Well and No Anxiety
1	0.305	0.397	0.180	0.577	0.099	0.500	0.555	0.146	0.441	0.216
2	0.457	0.265	0.359	0.577	0.197	0.250	0.139	0.292	0.276	0.216
3	0.457	0.265	0.359	0.144	0.394	0.250	0.277	0.292	0.331	0.323
4	0.457	0.265	0.359	0.433	0.394	0.250	0.277	0.292	0.331	0.323
5	0.152	0.265	0.359	0.144	0.099	0.250	0.139	0.438	0.221	0.323
6	0.152	0.397	0.359	0.144	0.394	0.250	0.555	0.292	0.276	0.431
7	0.305	0.265	0.180	0.144	0.099	0.250	0.139	0.292	0.386	0.323
8	0.152	0.397	0.359	0.144	0.394	0.500	0.277	0.438	0.110	0.431
9	0.305	0.397	0.180	0.144	0.394	0.250	0.139	0.292	0.386	0.323
10	0.152	0.132	0.359	0.144	0.394	0.250	0.277	0.292	0.276	0.108

S2: The number of criteria related to employee TOI differ from each other, thus leading to inconsistent comparisons between criteria. In order to standardize the data, Vector Normalization has been used to eradicate

inconsistency of data for its popularity for providing consistent outcomes and helping decision makers come out with optimal solution [7].

S3: Characteristics proportion will be computed for all academic employees implying the probability of a single criteria on TOI for an academic employee over all academicians. The value of the characteristics proportion lies between 0 to 1 .

S4: Entropy value calculation and weight assignment: The entropy value for each criteria has been calculated using the following formula :

1. Entropy e_j :

$$e_j = - \sum_{i=1}^n p_{ij} \cdot \log(p_{ij}) \quad (12)$$

Where:

- p_{ij} is the probability of the j th feature in the i th row.
- n is the number of rows (data points).

2. Weight $w_{e1}(j)$:

$$w_{e1}(l) = \frac{(1 - E_l)}{\sum_{l=1}^a (1 - E_l)} \quad (13)$$

Where:

- E_l is the entropy for feature l .
- a is the number of features (columns).

3. Weight $w_{e2}(l)$:

$$w_{e2}(l) = \frac{1/E_l}{\sum_{l=1}^a 1/E_l} \quad (14)$$

Where:

- E_l is the entropy for feature j .

4. Final Weight $w_e(l)$:

$$w_e(l) = X \cdot w_{e1}(l) + Y \cdot w_{e2}(l) \quad (15)$$

Where:

- X and Y are the weights assigned to $w_{e1}(l)$ and $w_{e2}(l)$, respectively.
- $X + Y = 1$.

Table 9. Results of entropy-based computation

Feature Name	Entropy e_j	Weight $w_{e1}(j)$	Weight $w_{e2}(j)$	Final Weight $w_e(j)$
satisfied compensation	0.957687	0.115239	0.100519	0.107879
satisfaction with workload	0.981912	0.049261	0.098039	0.073650
satisfied with job profession	0.982542	0.047547	0.097976	0.072761
working hour	0.908170	0.250096	0.105999	0.178048
Work tenure	0.943381	0.154201	0.102043	0.128122
Gender	0.978838	0.057634	0.098347	0.077990
Education	0.939794	0.163969	0.102433	0.133201
Good relationship with peers	0.985212	0.040274	0.097710	0.068992
Job position	0.978749	0.057877	0.098356	0.078116
Mentally well and do not have anxiety	0.976536	0.063904	0.098579	0.081241

3.11. TOPSIS and Interval Scaled Categorization

In the following steps, traditional TOPSIS has been applied for ranking employees according to turnover intention, and interval scaling has been used to categorize employees into three classes, as mentioned above.

S1: Construction of a weighted normalized matrix The normalized matrix is multiplied by entropy weights. The weighted normalized value for each criterion j , denoted as v_{ij} , is calculated as:

To normalize the data for each criterion j , the formula for vector normalization is:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum x_{ij}^2}} \quad (16)$$

where:

- x_{ij} : For j th feature or criteria, original value of employee i .
- r_{ij} : Normalized value.
- n : Number of employees.

S2: Characteristics Proportion The proportion p_{AB} for each criterion B across all employees is computed as:

$$p_{AB} = \frac{r_{AB}}{\sum r_{AB}} \quad (17)$$

where:

- r_{AB} : Normalized value for the A-th employee and B-th criteria.
- r_{AB} : Sum of all normalized values for criterion B.

S3: Entropy Value Calculation Entropy for each criterion l , denoted as e_l , is calculated using equations 12, 13, 14 and 15.

S4: Weighted Normalized Decision Matrix The weighted normalized value for each criterion j , denoted as v_{ij} , is calculated as:

$$v_{ij} = r_{AB} \cdot w_e(j) \quad (18)$$

where:

- r_{AB} : Normalized value for the A-th employee and B-th criterion.
- $w_e(j)$: Weight for the j -th criterion.

S5: Measurement of Positive and Negative Ideal Solutions Positive and negative ideal solutions are measured based on the formalization below:

- **Positive Ideal Solution (PIS):** Takes higher values for benefit criteria and lower values for cost criteria. According to equation 6.
- **Negative Ideal Solution (NIS):** Takes lower values for benefit criteria and higher values for cost criteria. According to equation 7.

S6: Separation Distance Measurement Euclidean distance measurement is used to find the separation distance from positive and negative ideal solutions:

$$S_i^+ = \sqrt{\sum (v_{ij} - v_j^+)^2} \quad (19)$$

$$S_i^- = \sqrt{\sum (v_{ij} - v_j^-)^2} \quad (20)$$

S7: Measurement of Relative Closeness to Ideal Solution and Categorization

Table 10. Ideal Solutions, Distances, and Closeness Coefficient (CTIS) for Employees

Employee	Positive Ideal Solution(PIS)	Negative Ideal Solution(NIS)	Distance to PIS (S_i^+)	Distance to NIS (S_i^-)	CTIS
Employee 1	0.7763	0.0973	1.0035	0.8970	0.4723
Employee 2	0.6716	0.1490	0.9440	1.0463	0.5257
Employee 3	0.9241	0.3097	1.0978	0.9342	0.4594
Employee 4	0.6720	0.4480	0.9636	1.0694	0.5257
Employee 5	0.3200	0.1600	0.7931	1.0060	0.5595
Employee 6	0.3920	0.1960	0.7314	0.9659	0.5697
Employee 7	0.4019	0.1346	0.7516	0.9244	0.5523
Employee 8	0.4627	0.3081	0.8612	0.8693	0.5028
Employee 9	0.3077	0.3077	0.9600	0.9319	0.4930
Employee 10	0.3920	0.3920	0.8437	1.0302	0.5499

The relative closeness to the ideal solution is measured as:

$$CTIS_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (21)$$

Now since the categorization has three classes namely Enthusiastic, behavioral and distressed, the importance interval score for employee categorization is computed based on the distance formula, where distance is computed using:

$$D = \frac{\max(CC_i) - \min(CC_i)}{N} \quad (22)$$

where:

- D : Distance between categories.

Employee Categorization: The academic employee turnover intention has been categorized into three classes based on the distance formula D . The categorization into enthusiastic, behavioral and distressed is given as below:

Table 11. Employee Classification Based on I-score Range Values

Employee Categorization	I-score Range	I-score Range Values	Employee
Distressed	$[minR, minR + D]$	(0.2587, 0.3938]	Employee 1, Employee 2, Employee 7
Behavioral	$(minR + D, minR + 2D]$	(0.3938, 0.5289]	Employee 3, Employee 4, Employee 8, Employee 9
Enthusiastic	$(minR + 2D, maxR]$	(0.5289, 0.6641]	Employee 5, Employee 6, Employee 10

3.12. Computational Complexity Analysis of Proposed and existing entropy-based method

This subsection compares the computational burden of the proposed AHP-Modified TOPSIS with De-Pareto segmentation and the entropy-based baseline. The comparison is reported in terms of asymptotic time complexity to show how both approaches scale when the number of employees increases. In this analysis, the pairwise criteria count is represented by N , while the number of employees is represented by K .

Let K be the number of employees and N be the number of criteria.

For the proposed method, the hybrid log-linear AHP stage introduces an $O(N^2)$ term, while decision matrix construction and multi-distance TOPSIS operations contribute $O(KN)$. The final ranking and segmentation step contributes $O(K \log K)$ because sorting is required before assigning productivity-oriented categories. The component-wise details are summarized in Table 12.

Table 12. Complexity breakdown of the proposed AHP-Modified TOPSIS with De-Pareto segmentation

Component	Complexity
Pairwise matrix & normalization (Hybrid Log-Linear)	$O(N^2)$ for AHP matrix + $O(N)$ normalization
Weight extraction & consistency check	$O(N^2)$ eigen computations
Modified TOPSIS decision matrix, weighted normalization	$O(KN)$
Composite distance calculation (Euclidean + Manhattan + Chebyshev)	$O(KN)$
Closeness score computation + Pareto segmentation	$O(K \log K)$ for ranking

$$T_{\text{Proposed}} = O(N^2 + KN + K \log K)$$

Since N is fixed, it can be rewritten as :

$$T_{\text{Proposed}} = O(K \log K)$$

This indicates that, for a fixed criteria set, the dominant computational cost in the proposed pipeline is the ranking step used for segmentation. In practical terms, the method remains computationally tractable for moderate-to-large institutional datasets while offering better decision robustness through multi-distance modeling and consistency-aware weighting.

For the entropy-based baseline, most operations are linear in both K and N . Unlike the proposed approach, interval-based class assignment does not require sorting, so no logarithmic ranking term appears. The baseline complexity components are summarized in Table 13.

Entropy + Standard TOPSIS + Interval Scaling (Existing Baseline)

Table 13. Complexity breakdown of the entropy-based TOPSIS interval-scaling baseline

Component	Complexity
Entropy weight calculation	$O(KN)$ for probability + log entropy computations
Normalization (Vector)	$O(KN)$
Standard TOPSIS (Euclidean only)	$O(KN)$ for PIS/NIS + distances
Interval-based classification	$O(K)$ (no sorting required)

$$T_{\text{Baseline entropy}} = O(KN)$$

Proposed modified TOPSIS based approach shows slightly more time complexity in contrast to entropy-based weighted approach.

4. EVALUATION METHODOLOGY

In this section, the proposed and existing scheme's methodology has been described to evaluate the schemes. The proposed and existing schemes were evaluated using Python version 3.9 on Google Colab, employing libraries such as Pandas, NumPy, Matplotlib, Seaborn, Scikit-learn, and Imbalanced-learn (SMOTE) to perform data preprocessing, visualization, model training, and evaluation. The experimental results have been carried out on an Intel(R) Core(TM) i7-8565U CPU @ 1.80GHz 1.99 GHz and 8 GB of RAM on a 64-bit operating system, Windows 10.

4.1. Random Forest as Baseline Classifier

The number of features selected using novel modified TOPSIS feature selection and individual traditional feature selection method was implemented using the Random Forest classifier model. The reason behind the selection of the Random Forest classifier as a baseline is described as follows:

1. **Versatility:** RF uses several decision trees for trained dataset to implement the ensemble method. Random Forest is well known to work well for different types of data [13], confirming the versatility of the classifier model without the necessity of using any type of scaling.

2. **Ability to cope with noise or outliers:** The Random Forest classifier is excellent at handling outliers or noise [6]. This makes it ideal for systems such as intrusion detection in contrast to other classifier models.
3. **Ability to work with imbalanced data:** The academic employee turnover intention dataset is an imbalanced dataset, and the Random Forest classifier model has been proven to work best with imbalanced datasets in modern era applications [19]. Hence, choosing Random Forest as a baseline classifier model allows the dataset to work optimally.

Since the collected primary dataset has different types of data and the dataset is imbalanced, the Random Forest classifier has been implemented as the baseline classifier to predict the performance metrics for different types of employee categorization according to TOI.

4.2. Performance Metrics

Confusion metrics has been used in order to evaluate and maximize employee turnover intention prediction. The “Confusion Matrix” is composed of the following four components:

- **True Positive (TRUPOS):** If the algorithm predicts academic employee TOI as “YES” and the actual label of employee TOI is also “YES”.
- **False Positive (FALPOS):** If the algorithm predicts academic employee TOI as “YES” but the actual label of employee TOI is “NO”.
- **True Negative (TRUNEG):** If the algorithm predicts academic employee TOI as “NO” and the actual label of employee TOI is also “NO”.
- **False Negative (FALNEG):** If the algorithm predicts academic employee TOI as “NO” but the actual label of employee TOI is “YES”.

The accuracy, F1 score, and Matthews correlation coefficient (MCC) are calculated using the following formulas:

4.2.1. Accuracy

The classifier’s accuracy is defined as the correct prediction of the total number of academic employees intending to leave the organization:

$$\text{Accuracy} = \frac{\text{TRUPOS} + \text{TRUNEG}}{\text{TRUPOS} + \text{TRUNEG} + \text{FALPOS} + \text{FALNEG}} \quad (23)$$

4.2.2. F1 Score

$$\text{F1} = 2 \times \frac{\text{PREC} \times \text{RECA}}{\text{PREC} + \text{RECA}} \quad (24)$$

Where:

- $\text{PREC} = \text{Precision} = \frac{\text{TRUPOS}}{\text{TRUPOS} + \text{FALPOS}}$
- $\text{RECA} = \text{Recall} = \frac{\text{TRUPOS}}{\text{TRUPOS} + \text{FALNEG}}$

4.2.3. Matthew’s Correlation Coefficient (MCC)

$$\text{MCC} = \frac{(\text{TRUPOS} \cdot \text{TRUNEG}) - (\text{FALPOS} \cdot \text{FALNEG})}{\sqrt{(\text{TRUPOS} + \text{FALPOS})(\text{TRUPOS} + \text{FALNEG})(\text{TRUNEG} + \text{FALPOS})(\text{TRUNEG} + \text{FALNEG})}} \quad (25)$$

5. EXPERIMENTAL RESULTS AND DISCUSSION

The categorized dataset using interval scaling and the De-parteo principle is split into training and test data with a 70:30 split, respectively. To evaluate the experimental results, various performance metrics such as accuracy, MCC, and F1 score have been used. Table 11 presents the experimental results for the proposed and existing permutation based scheme, while comparing the approach with traditional and Weighted sum model (WSM) using the Random Forest classifier as the base model.

Table 14. Experimental Results for Proposed and Existing Schemes

Category	Method Used for Ranking	Accuracy	F1-score	MCC
Distressed (20%)	Modified TOPSIS (Proposed)	0.9882	0.9881	0.9768
	Standard TOPSIS	0.9735	0.9728	0.9495
	Weighted Sum Model (WSM)	0.9523	0.9510	0.9102
	Entropy-based Method	0.9167	0.9190	0.8347
Behavioral (30%)	Modified TOPSIS (Proposed)	0.9566	0.9561	0.9134
	Standard TOPSIS	0.9420	0.9395	0.8862
	Weighted Sum Model (WSM)	0.9320	0.9290	0.8725
	Entropy-based Method	0.9073	0.8998	0.8238
Enthusiastic (50%)	Modified TOPSIS (Proposed)	0.9801	0.9798	0.9606
	Standard TOPSIS	0.9632	0.9610	0.9327
	Weighted Sum Model (WSM)	0.9498	0.9472	0.9079
	Entropy-based Method	0.9245	0.9221	0.8505

From the table above, the experimental results indicate that the proposed Modified TOPSIS method outperforms the Permutation-based Entropy approach across all categories (20%, 30%, and 50%). Notably, the accuracy and F1 scores remain consistently higher for the Modified TOPSIS, signifying its robustness in predicting employee categorization. The Matthews Correlation Coefficient (MCC) further substantiates the efficiency of the proposed scheme, showcasing superior predictive reliability. Figures above represents the prediction performance of categorized employee TOI with different performance metrics. From the results, it is clearly visible that proposed scheme outperforms the existing permutation based scheme, traditional TOPSIS scheme as well as weighted sum model (WSM).

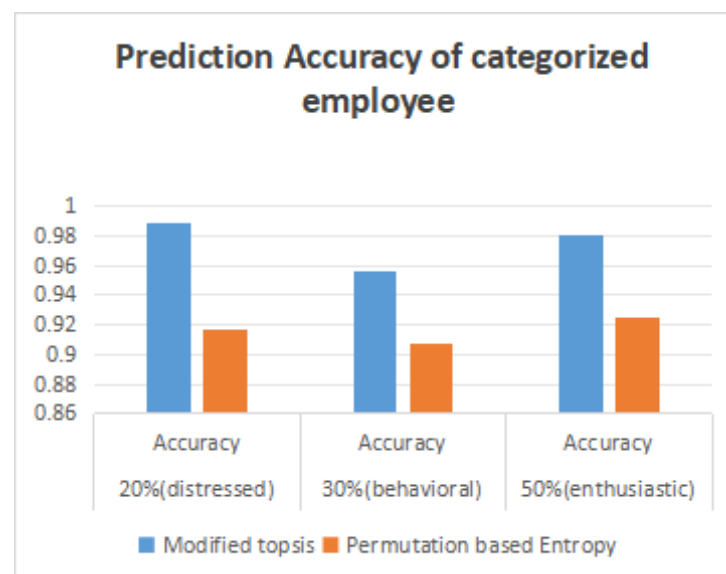


Figure 3. Comparison Chart of Accuracy for Proposed (Modified TOPSIS) and Existing (Permutation-based Entropy) Schemes

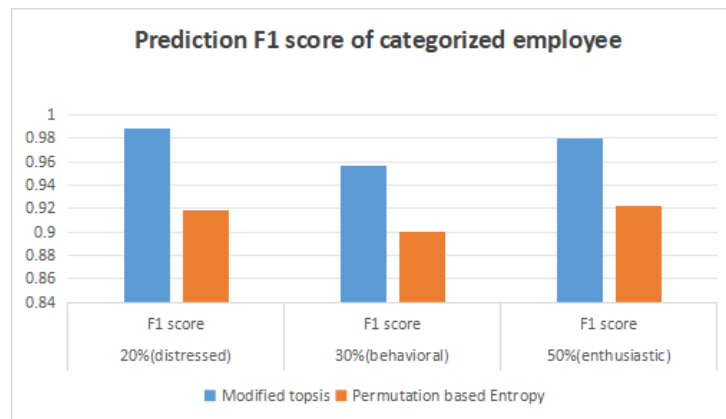


Figure 4. Comparison Chart of F1 score for Proposed (Modified TOPSIS) and Existing (Permutation-based Entropy) Schemes

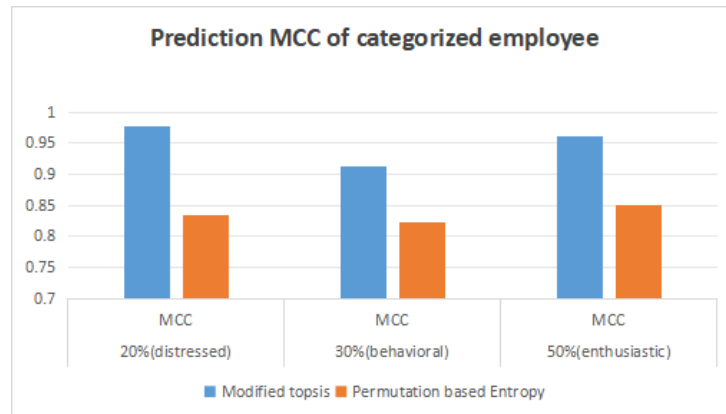


Figure 5. Comparison Chart of MCC for Proposed (Modified TOPSIS) and Existing (Permutation-based Entropy) Schemes

5.1. Sensitivity Analysis of AHP Weights

In order to investigate the robustness of the proposed approach to changes of weight in expert judgement, AHP weight vector from Table 5 was perturbed using $(1 + \epsilon_j)$, where ϵ_j was randomly sampled by $\pm 5\%$ and $\pm 10\%$ using multiplicative factor $(1 + \epsilon_j)$. For each perturbation level, 100 random weight variations were generated and normalized for summing up to 1. A recalculation of modified TOPSIS was accomplished and ranks of employees were compared to the original baseline using Spearman correlation and category transition counts.

Table 15. Sensitivity analysis of the proposed approach while perturbation of the weight of AHP

Perturbation	Mean Spearman ρ	Min ρ	Average category changes	Max category changes
$\pm 5\%$	0.974	0.958	1.4 employees	4 employees
$\pm 10\%$	0.948	0.921	3.1 employees	7 employees

In every case, correlations remained high, representing a strong stability in ranking employees according to turnover intention. There was no switching of employees between enthusiastic to distressed and vice versa. While most employee rank movements occurred near the behavioral employee group threshold, the shifts remain marginal, thus proving the stability of the approach by applying moderate variations in subjective weights. Thus, this approach is reliable for real world managerial use.

5.2. Discussion

It can be clearly seen from the results above that AHP-modified TOPSIS and Pareto principle outperforms existing permutation based, traditional TOPSIS and weighted sum approach. Although modified

TOPSIS exhibits slightly more time complexity in contrast to traditional TOPSIS and existing entropy-based weighted approach, AHP-modified TOPSIS-Pareto principle exhibits greater performance in all aspects. Our proposed approach ensures the reduction of extreme values as mentioned in step 2 of section 3.6. Furthermore, to mitigate the impact of extreme values, the integration of distance metrics was transformed using natural logarithmic function in step 7 of section 3.7 which is consistent with prior empirical research [27], which incorporated logarithmic transformation for reducing the outlier influence. The synergy of step 2 of section 3.6 and step 4 of section 3.7 in proposed algorithm reduces the impact of extreme values empirically and improves the overall performance metrics of the proposed approach in contrast to existing approach. This finding is in line with prior research work by [28] who showed that addressing abnormal or extreme instances within the minority class leads to improved classification performance across F1-score and MCC metrics, meaning the issue of resolving extreme values is related with higher performance achievement.

In addition, the perturbation of subjective weights of AHP in section 5.1 is shown to have marginal or minimum impact on employee categorization, meaning the perturbation of weights do not change the employee categorization drastically, consequently providing the stability of the approach.

So, the findings suggest that AHP-modified TOPSIS-Pareto principle provides a time performance tradeoff for categorizing employees according to turnover intention when compared with traditional approaches.

6. CONCLUSION

In this article, AHP, modified TOPSIS and Depareto principle have been used to classify employee TOI into enthusiastic, behavioral and distressed. On the other hand, existing scheme has been utilized to categorize employees into same categories. The proposed approach highlights three aspects. Firstly, a modified TOPSIS approach with integrated feature selection using information gain, RFE and Select K-best has been used to find out the topmost features for detecting employee TOI. Secondly, an AHP-Modified TOPSIS has been proposed for ranking employees according to TOI and categorize employees using Depareto principle. Finally, the categorization of employee TOI is compared with proposed and existing scheme of entropy-based approach, traditional TOPSIS and weighted sum model. A primary dataset collected from academic employees have been collected for implementing proposed and existing schemes. Proposed and traditional existing methods have been categorized into several performance metrics namely accuracy, F1 score, MCC. Simultaneously, the time of proposed and existing schemes have been calculated. Although proposed approach exhibits slightly more time complexity compared to existing approaches, the proposed approach is the best choice in terms of time performance metrics tradeoff compared with the existing methods. Among the employees within an organization, the most productive employees are the enthusiastic ones. So, detecting top 20% employees accurately within an organization helps identifying the most productive academic employees and retaining them. On the contrary, the loss of high quality and productive academicians influence the skills and capabilities of students, thus hampering the overall organizational performance. So, it is imperative for a university rector to accurately detect and prevent the ultimate turnover of the most productive enthusiastic employees to ameliorate the motivation and morale of the academic community. As illustrated in Table 5, using Modified TOPSIS revealed different factors such as work meaningfulness, work-life balance, compensation satisfaction, mental well-being and kinship support to be the important retention factors. A university rector can pay attention to these factors to retain the most valuable employees.

The proposed scheme shows superiority in terms of time performance tradeoff over traditional existing TOI and it is expected to perform well in similar academic datasets for detecting employee TOI. However, in future, this approach can be tested against real time dataset from other organizations.

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