IDENTIFYING EMPLOYEE PROFILES ASSOCIATED WITH TURNOVER INTENTIONS: A K-MEANS CLUSTER ANALYSIS OF PSYCHOLOGICAL AND JOB-RELATED FACTORS

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DOI: 10.24818/MSWP.2026.07

Abstract: *The purpose of this study is to examine the impact of a set of factors such as organization-based self-esteem, job satisfaction, job meaningfulness, and job insecurity on the turnover intention. Organizations often rely on the human resources department to pinpoint the critical factors that lead to employee turnover. For this study, data was collected from 277 Romanian employees using a questionnaire shared on multiple social media channels from October to November 2025. Using K-means cluster analysis, employees were segmented into three distinct groups based on their perceptions, highlighting patterns of engagement and potential turnover risk. The results of the study show that employee retention varies significantly across the three identified clusters. Cluster 2, characterized by high salary, strong job satisfaction, high self-esteem, low insecurity, and high perceived job meaningfulness, presents the lowest turnover risk, with only 7% actively seeking new employment. Cluster 1 shows moderate levels across these variables and ambiguous turnover intentions, with approximately 43% of employees exploring new job opportunities, indicating that targeted interventions could meaningfully reduce turnover in this group. In contrast, Cluster 3 represents employees with low satisfaction, high insecurity, low perceived meaningfulness, and low self-esteem, where 76% are actively seeking a new job, signaling an urgent need for retention strategies or separation planning. Based on the results, practical recommendations are provided for managers and human resources professionals in order to enhance work engagement and reduce organizational turnover. This study contributes to literature by integrating psychological and job-related factors with cluster-based segmentation and analysis to gather strategies for workforce retention.*

Keywords: turnover intention, organizational self-esteem, k-means clustering, job security, job meaningfulness, employee behavior.

JEL Classification: M12, M54, J63, C38.

1. Introduction

The modern world is undergoing continuous digitalization, which is leading organizations to adopt data-driven decision-making processes and strategies. Departments across modern enterprises rely on historical data and analytical dashboards to justify their strategic choices. Furthermore, the influence of artificial intelligence and machine learning has become increasingly evident, with a growing number of companies integrating decision systems based on artificial intelligence in order to reduce human cognitive biases. At the same time, employee retention and turnover remain critical organizational challenges. Replacing an employee entails substantial financial and temporal costs, from recruitment and onboarding to productivity ramp-up periods. Considering these factors, the implementation of data-driven approaches presents an opportunity to address employee attrition in a more effective way.

In this context, we propose the development of a machine learning model, using k-means clustering, to categorize employees into different groups. K-means clustering is an unsupervised machine learning algorithm used to partition a dataset into a predefined number of groups, called clusters, based on similarity among data points. The clusters used in this study will be examined to assess their likelihood of leaving the organization and to identify the key determinants influencing turnover intention. Potential predictive variables include salary satisfaction, job satisfaction, organizational self-esteem, perceived job insecurity and meaningfulness. Such an analytical framework enables managers and human resources professionals to proactively identify at-risk employee groups and intervene with targeted retention strategies. By doing so, organizations can mitigate turnover costs and retain high-performing talent, ultimately fostering a more stable and engaged workforce.

2. Literature review

2.1. Factors influencing turnover intention in employees

There are many reasons why an employee may leave their workplace, such as personal circumstances, organizational factors, or unequal treatment (Kamalaveni, Ramesh and Vetrivel, 2019). It is very important for organizations to identify the factors that contribute to low employee retention and an increased intention to quit, so they can proactively implement strategies that can reduce turnover and create a more stable and supportive work environment. Organizations understand that maintaining employee engagement and retention are essential to their success in the dynamic and competitive business world of today (Farooqi et al., 2024). Moreover, the recent Covid-19 pandemic has fundamentally reshaped the way organizations operate, altering managerial implications and transforming traditional work structures through the widespread adoption of remote work. During the pandemic, people reassessed their values and life priorities, bringing greater attention to job satisfaction as a key determinant of employee retention. Job satisfaction fosters the expression of positive emotions and behaviors. When employees feel a sense of belonging within their team and perceive that their personal values align with those of the organization, they tend to exhibit higher levels of organizational commitment, and, therefore, lower turnover. Workplaces that cultivate an organizational culture promoting a supportive and positive work environment hold a significant advantage in fostering higher levels of employee involvement and commitment (Pevec, 2023).

Many factors affect human resources in any organization. These factors differ from one company to another company, but they can be predicted by broad factors that have been proposed in various theories, developed by human resource management experts, drawing on both practical experience and research findings (Junaidi et al., 2020). Studies have identified employee turnover intentions through eight factors, such as quality of management practices, low salary, no career growth opportunity, lack of support from the peers, supervisors and family members, little learning opportunities, poor working environment (no workplace safety), communication and job insecurity (Kamalaveni, Ramesh and Vetrivel, 2019). Job insecurity usually refers to the subjective perception that one's current job may be lost involuntarily, and it has been shown consistently to increase turnover intentions. Even though the turnover intention can be seen as a deliberate choice that an employee makes when trying to cope with an unfavorable situation, it also involves uncertainty about their future employment. The characteristics of a potential new job remain unknown, making it challenging for employees to anticipate and plan ahead, interfering with long-term commitments such as marriage, having children or purchasing residential property (Balz and Schuller, 2018). Another factor that shapes an employee's decision to stay or leave is the performance appraisal process, as it enhances both monetary rewards and non-monetary benefits such as recognition, career development opportunities and managerial support (Kamalaveni, Ramesh and Vetrivel, 2019).

Moreover, studies have found that meaningful work had large correlations with work engagement, commitment and job satisfaction, suggesting that meaningful work may either reflect the same underlying construct or serve as a more immediate driver of these outcomes. It has also been proposed that meaningful work enhances wellbeing outside the workplace, including variables such as life satisfaction, negative affect and general health (Allan et al., 2018). When the output achieved by an organization falls below expectations, employees tend to feel dissatisfied. Another important factor is that personal satisfaction, a sense of individual achievement, and the fulfillment of long-term personal goals all contribute to higher satisfaction, which in turn strengthens employee retention. Studies revealed that there is a negative relationship between organizational support and satisfaction and turnover, and poor salary is mentioned as one of the reasons to leave an organization (Shakeel and But, 2015). Salary is one of the most frequently examined predictors of turnover intention, and most studies show a clear negative relationship: when salary or pay satisfaction rises, employees' desire to leave tends to fall (Aman-Ullah et al., 2022). The link is rarely direct, salary works largely through psychological mediators such as job satisfaction, affective commitment, work engagement, job attachment and burnout (Saeed et al., 2023). Research also distinguishes between pay level and pay satisfaction: even where absolute wages are constrained, increasing satisfaction with pay structure, raises and benefits still lowers turnover, especially when combined with enriched jobs and perceived organizational support (Aman-Ullah et al., 2022). At the same time, salary is only one element in a broader retention system: workload, supervision quality, work environment, work-life balance, and career development can either strengthen or undermine the impact of pay in staying or leaving (Dibiku, 2023).

2.2. K-means cluster analysis in organizations

As information technology continues to advance, researchers have turned to a range of machine learning approaches to boost the results achieved in human resource management (Zhao et al., 2019). Machine learning offers numerous benefits to human resource management, including improved decision-making, better resource allocation, cost efficiency and enhanced information processing. One of its most important advantages is its ability to support anticipatory decision-making. By analyzing data patterns, organizations can detect potential challenges early and take action before the issues escalate (Nalla, 2025).

Clustering is one of the most widely used techniques for forecasting, as it groups data based on shared characteristics and maximizes similarity within each group. As a form of unsupervised learning, clustering operates on unlabeled datasets and uncovers hidden structures or patterns that would otherwise remain unnoticed. Owing to its ability to reveal meaningful groupings, cluster analysis is widely applied across various domains, including market research, prediction, image processing, pattern recognition and broader data analysis tasks, making it a valuable tool for extracting actionable insights from complex datasets (Fadhil, 2021). K-means is one of the most well-known clustering algorithms, valued for its simplicity and efficiency. The user chooses a number of clusters, K, and the algorithm repeatedly divides the data into these K groups based on a distance measure. It begins by randomly selecting K points as initial cluster centers. Then, each data point is assigned to the nearest center, forming initial clusters. After this, the centers are recalculated using the points within each cluster. The cycle continues until the algorithm meets a stopping condition, such as when the cluster centers no longer change significantly (Zhao, 2020). Considering that organizations often use satisfaction surveys to support employee retention efforts (Shakeel and But, 2015), the resulting data can be further analyzed using clustering algorithms to identify meaningful patterns and develop more targeted improvement strategies.

2.3. Research questions

Based on the theoretical framework and the variables discussed, the present study aims to explore how different workplace-related factors are associated with employees' intention to leave their current job. In order to structure the empirical investigation and guide the analysis, a set of research questions were formulated.

RQ1. *What distinct employee profiles emerge from the combined responses to the five workplace related scales, along with demographic variables? How do these clusters differ in terms of the average scores across the five scales?*

RQ2. *To what extent are the identified clusters associated with employees' intention to leave the workplace?*

RQ3. *Can clustering techniques reveal subgroups of employees at higher risk of turnover that may not be identifiable through traditional descriptive analysis?*

3. Methodology

This study employs an exploratory research design integrating descriptive analysis and machine learning techniques to identify meaningful employee segments based on survey responses. The dataset consists of responses from Romanian employees to five validated scales: salary satisfaction, job satisfaction, job meaningfulness, organizational self-esteem and job insecurity, complemented by demographic variables and the target variable, intention to leave the workplace. The questionnaire was distributed via Google Forms between October and November 2025 through social media platforms.

3.1. Participants

The target population of this study consisted of employed individuals working in Romania, regardless of the industry, organization size, or job level. The inclusion criterion was having an active job at the time of data collection, while individuals without current employment were excluded from the analysis. The sample was obtained through convenience sampling, as the questionnaire was distributed across multiple social media platforms without targeting a specific subgroup. Although this approach limits the generalizability of the findings, it was deemed appropriate for an exploratory study aimed at identifying broad employee profiles rather than making population-level inferences.

Following the distribution of the questionnaire, 277 responses were collected from Romanian employees across various industries. Out of the respondents, 8 did not have a job and were, therefore, excluded. A total of 269 responses were retained for the final analysis. 55.4% of the respondents were female, while 44.6% were male. Regarding respondents' educational background, 14.86% had completed secondary or high school, 54.27% held a bachelor's degree, 29.73% had obtained a master's degree, and 1.11% possessed a doctoral degree. Information on monthly net income was also collected: 3% of respondents chose not to disclose their income, 8.17% earned less than 3000 RON, 26.4% earned between 3001 and 5000 RON, 29.37% between 5001 and 8000 RON, 17.85% between 8001 and 12000 RON, and 15.24% earned more than 12000 RON. The median total work experience of respondents was 5 years, with 45.72% working on-site, 37.17% in a hybrid arrangement, and 17.1% remotely.

3.2. Instruments

For this study, five scales adapted into Romanian from Research Central (https://researchcentral.ro/) were applied, all of which pertain to the field of Work and Organizational Psychology:

1. Pay Satisfaction Questionnaire (Scale 407), which contains 18 items (Heneman and Schwab, 1985). Of the 18 items, 5 items (1, 6, 10, 14, 15) were eliminated due to redundancy. The scale's internal consistency coefficient α was 0.922.
2. Job Satisfaction - Subscale from Michigan Organizational Assessment Questionnaire (Scale 428), which contains 3 items (Tepper, 2000). The scale's internal consistency coefficient α was 0.840.
3. The Work and Meaning Inventory (Scale 483), which contains 10 items (Steger, Dik and Duffy, 2012). The scale's internal consistency coefficient α was 0.877.
4. Organization-Based Self-Esteem (Scale 416), which contains 10 items (Pierce et al., 1989). The scale's internal consistency coefficient α was 0.933.
5. Global Qualitative Job Insecurity Scale (Scale 421), which contains 4 items (De Witte et al., 2010). The scale's internal consistency coefficient α was 0.934.

Based on the internal consistency results, no items were dropped from each scale.

3.3. Data analysis

In this research, the analysis of the data obtained from the distribution of the questionnaire was conducted using both quantitative statistical methods and machine learning techniques. The data analysis followed several stages, beginning with data cleaning, standardization using StandardScaler, and determination of the optimal number of clusters via the Elbow Method, continuing with K-means clustering, cluster characterization through mean score comparison, PCA-based visualization, and descriptive analysis of turnover intention across clusters. The open-source platform JASP (version 0.19.3.0) and the Python programming language (version 3.10.4) were used, with libraries such as Pandas, NumPy, Scikit-learn, and Seaborn.

4. Results

Clustering algorithms do not require normally distributed variables; hence normality tests were not conducted for the data. The clustering algorithm was applied using five variables: salary satisfaction, job satisfaction, job meaningfulness, organization-based self-esteem and job insecurity. First, the data was standardized to zero mean and unit variance (z-score standardization) (Mohamad and Usman, 2013) using Scikit-learn's built-in function, StandardScaler. Therefore, all the variables were transformed so that they have a mean of 0 and a standard deviation of 1, ensuring that each variable contributes equally to the clustering algorithm's distance computation. The optimal number of clusters was then explored using the Elbow Method, which evaluates how the within-cluster sum of squares (WCSS) changes as the number of clusters increases. The inflection point, called "elbow", provides an empirical indication of the most appropriate number of clusters for the data (Marutho et al., 2018; Nainggolan et al., 2019). Although the elbow in the WCSS curve, as seen in Figure 1, could visually suggest either 2 or 3 clusters, the reduction in WCSS between 2 and 3 clusters remains significant. After 3 clusters, the decrease becomes much more gradual, indicating decreasing returns from adding additional clusters. Additionally, using only 2 clusters would oversimplify the behavioral patterns present in the data by merging distinct groups. Therefore, choosing three clusters provides a better balance between reducing within-cluster variance and maintaining meaningful segmentation. The clustering solution was additionally evaluated using the Silhouette Score, an internal validity index that summarizes within-cluster cohesion and between-cluster separation (Rousseeuw, 1987; Shahapure and Nicholas, 2020), resulting in a value of 0.266. The value indicates moderate cluster separation, suggesting that the identified groups are distinguishable, although some overlap exists between them. Given the complexity and continuous nature of psychological data, perfect separation between clusters is rarely expected.

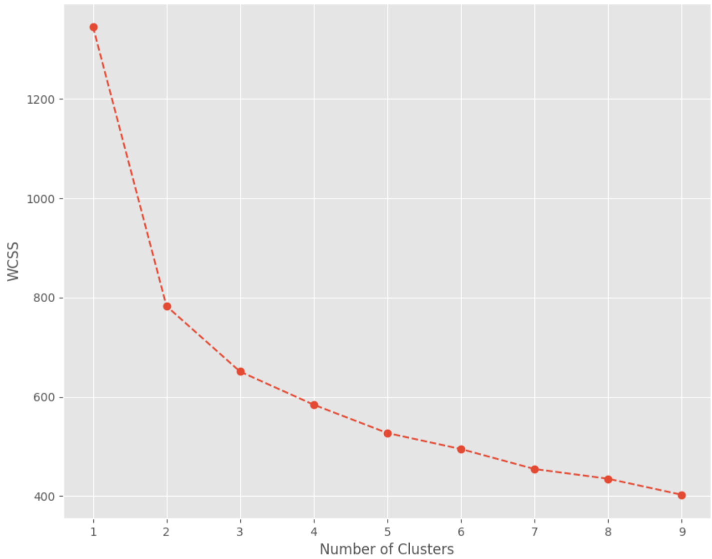

Fig. 1. Elbow Method

Source: Author's own analysis using Python 3.10.4.

K-means clustering was applied to the standardized dataset in order to identify underlying groups of employees with similar response patterns. To characterize the three clusters identified by the K-means algorithm, the mean values of each scale were calculated for each cluster, allowing for a clear interpretation of the distinct profiles emerging for the analysis. Table 1 presents the average scores of the five scales for each cluster, highlighting the differences in patterns of employee responses. One-way ANOVA confirmed that differences across clusters were statistically significant for all five clustering variables: salary ($F = 95.342$, $p < .001$), job self-esteem ($F = 169.986$, $p < .001$), job satisfaction ($F = 222.190$, $p < .001$), job insecurity ($F = 137.977$, $p < .001$) and job meaningfulness ($F = 117.053$, $p < .001$).

Table 1

Scale scores for each cluster and ANOVA test

	Salary	**Job Self-esteem**	**Job Satisfaction**	**Job Insecurity**	**Job Meaningfulness**
Cluster 1	2.957	3.852	3.360	3.103	3.032
Cluster 2	3.960	4.560	4.176	1.668	3.801
Cluster 3	2.620	2.840	2.000	3.877	2.063
F	95.342	169.986	222.190	137.977	117.053
p	<.001	<.001	<.001	<.001	<.001

Source: Author's own analysis

To facilitate interpretation, the clusters were visualised in a two-dimensional space using Principal Component Analysis (PCA), highlighting the separation and distribution of observations across clusters, as seen in Figure 2. Principal Component Analysis (PCA) is a dimensionality reduction technique that transforms a set of correlated variables into a smaller number of uncorrelated components, capturing most of the variance in the data (Jolliffe and Cadima, 2016).

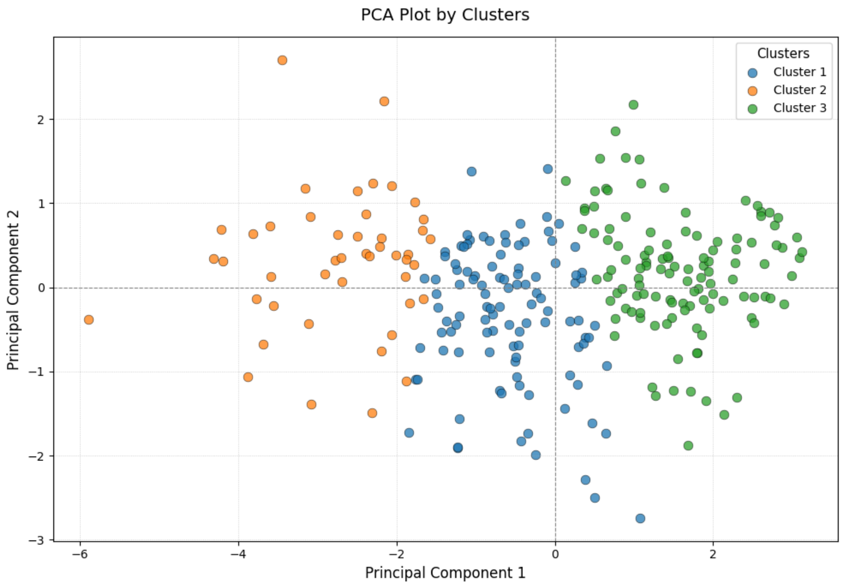

Fig. 2. Two-dimensional plot of the clusters

Source: Author's own analysis using Python 3.10.4.

The three clusters emerging from the analysis display distinct profiles, which are further examined in relation to each research question below.

RQ1: *What distinct employee profiles emerge from the combined responses to the five workplace related scales, along with demographic variables? How do these clusters differ in terms of the average scores across the five scales?*

Cluster 1 represents employees with moderate levels in most dimensions. Salary (2.96) and job satisfaction (3.36) are slightly above the lowest cluster, while self-esteem (3.85) and insecurity (3.10) are moderate. The perceived job meaningfulness (3.03) is also at an intermediate level, suggesting that this group has balanced but not outstanding perceptions. They are not highly insecure, but not extremely secure either. Cluster 2 represents employees with high overall scores and low insecurity. This cluster has the highest salary (3.96), esteem (4.56) and job satisfaction (4.18). Insecurity is notably low (1.67), and perceived meaningfulness is relatively high (3.80), indicating that these employees are likely the most confident, satisfied and fulfilled group. Cluster 3 characterizes employees with low scores in most dimensions. Salary (2.62), self-esteem (2.84), job satisfaction (2.00) and job meaningfulness are all the lowest among the three clusters. Insecurity is the highest (3.88), indicating that this group experiences more uncertainty and dissatisfaction, along with lower recognition and perceived meaning in their work. All these patterns indicate notable variation in employees' perceptions of their work environment and remuneration. Figure 3 presents the radar chart of the three employee clusters, illustrating their profiles across the scales.

In terms of demographic variables, there seem to be no notable differences in gender across the clusters, they are distributed fairly equal. Furthermore, work mode distribution is remarkably similar across clusters, with no notable differences between hybrid, remote or on-site roles. Based on the salary distribution, it seems like cluster 2 has the highest proportion of higher salaries, with 23.89% earning between 8001 – 12000 RON and 18.58% earning more than 12000 RON monthly. In this cluster, very few earn less than 3000 RON (2.65%), which matches their high job satisfaction, self-esteem and low insecurity. Financial compensation is usually consistent with perceived success. Cluster 1 has moderate salary distribution, with the largest percentages between 3001 – 5000 RON (31%) and 5001 – 8000 RON (28%). Some earn more than 12000 RON monthly (16.5%), likely being a few high earners that lift the average. Cluster 3 has the highest percentage of less than 3000 RON salaries (19%) and 5001 – 8000 RON (36%), while only 4% earn more than 12000 RON. Slightly surprising is that 36% fit into the 5001 – 8000 RON range, which could indicate that even those earning decent salaries might feel undervalued or insecure. Moreover, cluster 2 has the highest proportion of people with subordinates, while cluster 3 has the lowest proportion, consistent with lower salary and lower perceived influence at work.

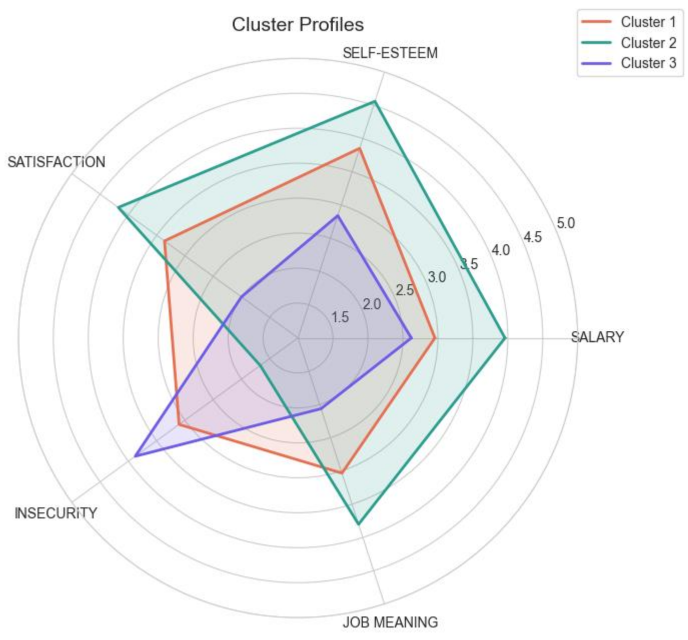

Fig. 3. Cluster profiles across scales

Source: Author's own analysis using Python 3.10.4.

RQ2: *To what extent are the identified clusters associated with employees' intention to leave the workplace?*

In the questionnaire, respondents were asked two questions: *Are you actively looking for a new job?*, recorded as a binary variable, and *How likely is it that you will leave your job in the next 6 months?*, with responses recorded on a five-point Likert scale ranging from "not at all likely" to "very likely". While the first question measures current, active turnover behavior, the second question measures potential or latent turnover intentions, capturing intentions that may not yet be translated into action. An employee might consider leaving if circumstances change, even without actively searching.

Based on the analysis conducted, the turnover behavior of the respondents aligns with the cluster characterization. Cluster 3 has the highest active job search, with 76.6% of respondents actively searching for a new job. This means that employees in this cluster are highly motivated to leave, which represents an immediate retention risk. Cluster 1 has moderate active job search (43.1%), reflecting their intermediate satisfaction and insecurity. Employees from cluster 2, the ones that are the most fulfilled at their workplace, also have the lowest active job search (7.1%). This cluster has high satisfaction, low insecurity, high salary, so very few employees are actively seeking new jobs. This indicates that the factors analyzed have a correlation with turnover intention.

Figure 4 shows the distribution of responses regarding latent turnover intentions over the next six months across the identified clusters. It is important to mention that turnover intention was not taken into account by the clustering algorithm. Instead, the clusters were formed exclusively on the five analyzed factors. The figure therefore only reflects the relationship between these factors and employees' intentions to leave the organization, displaying the percentage distribution of these responses within each cluster, allowing for a comparison of how the clusters differ in terms of their underlying risk of turnover.

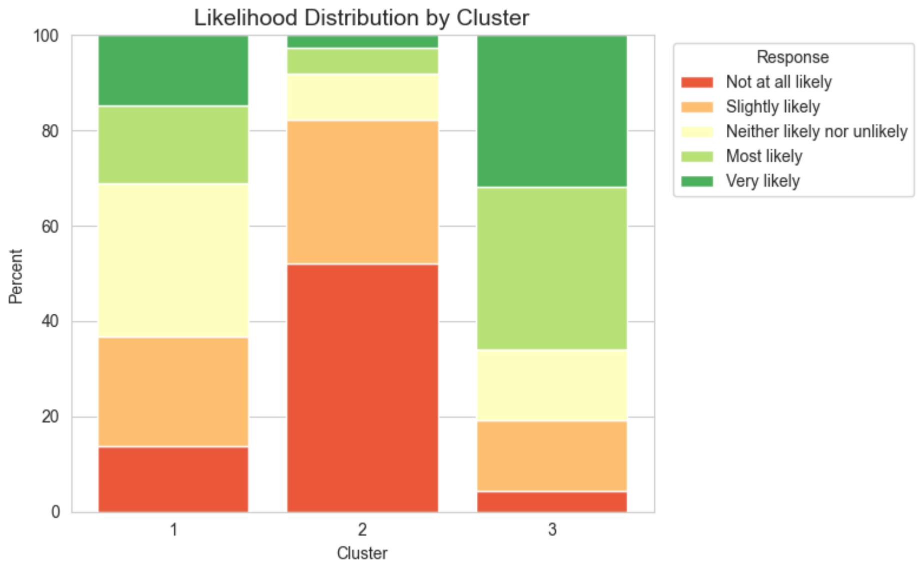

Fig. 4. Distribution of turnover intention likelihood across the three employee clusters

Source: Author's own analysis using Python 3.10.4

Cluster 3 represents the group at the highest immediate risk of turnover. Individuals in this cluster are actively searching for alternative employment opportunities and report a high likelihood of leaving their current organization. The distribution shows a strong concentration in the categories "most likely" and "very likely", indicating the clear intention to exit rather than just dissatisfaction. From a managerial perspective, this group requires urgent attention, although retention interventions may have limited effectiveness. Respondents in cluster 2 are not actively searching for new job opportunities, indicating a low likelihood of leaving. The responses are heavily concentrated in the "not at all likely" and "slightly likely" categories, reflecting a high degree of organizational attachment. This cluster consists of employees who are satisfied with their roles and working conditions, representing a low turnover risk group. Retention efforts for this segment may focus on maintaining engagement rather than addressing immediate concerns. Cluster 1 has a middle position between the two other clusters, displaying mixed or ambiguous intentions. The employees are not strongly committed to leaving, but they are not as stable as Cluster 2. A notable share of responses falls in the "neither likely nor unlikely" and "slightly likely" categories, which may indicate latent turnover intentions. The employees might not yet be actively searching for other opportunities, but certain workplace factors can push them toward considering leaving in the future. Cluster 1 can be an important target for proactive retention strategies, such as career development opportunities, improved communication and engagement initiatives.

To complement the descriptive analysis, Table 2 reports the results of the statistical tests confirming significant differences across clusters for both turnover intention variables. A chi-square test confirmed statistically significant differences across clusters in active job search behavior ($\chi^2 = 78.725$, df = 2, $p < .001$). A one-way ANOVA revealed significant differences across clusters in the likelihood of leaving within the next six months ($F(2, 266) = 59.446$, $p < .001$), further validating the distinction between the three employee profiles.

Table 2

Statistical tests for turnover intention across clusters

Variable	Test	Statistic	df	p
Active job search	χ^2	78.725	2	<.001
Likelihood of leaving in the next 6 months	F	59.446	2, 266	<.001

Source: Author's own analysis using Python 3.10.4.

RQ3: *Can clustering techniques reveal subgroups of employees at higher risk of turnover that may not be identifiable through traditional descriptive analysis?*

Fig. 5. Correlation between scales and turnover intention

Source: Author's own analysis using Python 3.10.4.

Classic descriptive analysis usually looks at employees as one big group, or by obvious categories. Clustering techniques group employees based on patterns in their data, not just one variable at a time, which can uncover hidden subgroups that wouldn't be spot through descriptive analysis. Figure 5 shows the correlation heatmap, which indicates that turnover intention is moderately negatively correlated with job satisfaction (-0.47), salary (-0.44), self-esteem (-0.37) and meaningfulness (-0.38), while showing a positive correlation with insecurity (0.39). Additionally, strong positive relationships can be observed between job satisfaction, meaningfulness, and self-esteem, suggesting that these factors tend to increase together.

The correlation heatmap shows several moderate relationships between turnover intention and the analyzed variables. However, correlation analysis only captures pairwise linear relationships and treats the sample as a homogeneous group, making it difficult to identify employees who share similar combinations of characteristics. The clustering algorithm revealed three distinct employee groups, each with different combinations of factors, highlighting varying levels of turnover risk. Some clusters displayed characteristics associated with higher turnover intention, such as lower job satisfaction and meaningfulness combined with higher insecurity. These patterns would be difficult to detect through traditional descriptive statistics alone, demonstrating that clustering techniques can reveal hidden subgroups of employees at greater risk of turnover.

5. Discussion

This research makes a significant contribution to literature by integrating findings from prior studies on critical factors in employee retention with the technical literature on clustering methods and algorithms. The analysis addressing RQ1 and RQ2 are consistent with existing research on the role of salary in employee behavior and turnover intentions (Kamalaveni, Ramesh and Vetrivel, 2019; Shakeel and But, 2015). Specifically, employees receiving higher monetary rewards tend to exhibit lower turnover intentions and higher levels of self-esteem, job-meaningfulness, satisfaction and lower insecurity. These results also align with Balz and Schuller's study (2018), highlighting the importance of workplace insecurity for both employee well-being and turnover intentions. Furthermore, the analysis of RQ3 supports Wardhani and Lhaksmana (2022), who demonstrated that employee retention can be predicted through machine learning methods, thereby reducing potential human bias.

Regarding the three clusters identified in the analysis, key differences among them suggest targeted managerial approaches to improve retention. Employees in Cluster 2 are stable, high-performing individuals with high salaries, strong job satisfaction, high self-esteem, and low insecurity. Only 7% of this group is actively seeking new employment. Management strategies should focus on maintaining their satisfaction, as losing these employees would significantly impact team performance. Cluster 1 represents employees with moderate well-being and ambiguous turnover intentions. Approximately 43% of these employees are looking for new job opportunities. They are not highly dissatisfied, but neither are they fully committed. This group is undecided and potentially easily influenced, making it the ideal target for well-designed interventions that could have a substantial positive impact. Strategies such as mentoring, coaching, and clearer communication about career paths could strengthen their engagement and reduce turnover risk. Cluster 3 is characterized by high turnover risk: 76% of employees are actively seeking new employment. They report low satisfaction, high insecurity, and overall dissatisfaction, signaling an urgent need for retention. Interventions for this group should focus on ensuring compensation fairness, enhancing job meaningfulness, and conducting stay interviews or pulse surveys to identify pain points.

The cluster profiles identified in the analysis are consistent with the existing literature on employee turnover and workplace well-being. Research shows that employees with moderate levels of well-being and satisfaction often display more unstable turnover intentions, as their attitudes might fluctuate in response to workplace stressors or changes in organizational conditions (Cha and Lee, 2022), similar to Cluster 1. Similarly, studies link high job satisfaction, strong self-esteem and higher salaries with lower turnover intentions (Nemteanu, Dinu and Dabija, 2021; Bae, 2023), which aligns with the characteristics of Cluster 2. In contrast, the profile observed in Cluster

3 reflects patterns widely reported in turnover research, where employees experiencing higher insecurity have stronger intentions to leave their jobs (Cha and Lee, 2022). Altogether, these parallels suggest that the clusters identified reflect theoretically supported employee profiles.

Based on these findings, organizations, managers, and human resources departments are encouraged to periodically deploy internal surveys, implement clustering algorithms trained on their internal data, and segment employees to identify areas for improvement. For instance, Cluster 2 employees require career progression opportunities to remain challenged, competitive salaries, and recognition for performance. These employees are the easiest to retain, but the costliest to lose. Cluster 1 would benefit from targeted mentoring or coaching to improve clarity and reduce insecurity, as well as better internal communication regarding career paths. Cluster 3 requires immediate interventions addressing structural dissatisfaction and insecurity to reduce turnover risk. This only shows the importance of personalized support for each employee.

6. Conclusions

Employee retention is a critical concern for organizations, relevant both to managers and human resources departments. The loss of employees represents a significant cost for organizations, not only financially but also in terms of time and productivity. Employees consider multiple factors when deciding whether to leave their jobs and addressing these factors proactively can influence their decisions and potentially prevent turnover. This research provides valuable insights for organizations, highlighting the importance of employee segmentation and delivering personalized support. Each employee may belong to a different group with distinct needs, and interventions should be tailored accordingly. The study also emphasizes the role of key factors such as salary, job satisfaction, job meaningfulness, self-esteem, and insecurity in shaping employees' turnover intentions.

However, several limitations should be acknowledged. The analysis is based on a specific dataset (n = 277), therefore the findings may not be fully generalizable to all industries or organizational contexts. Clustering techniques identify patterns within the data but do not establish causal relationships between variables and turnover intentions. Additionally, the variables included in the analysis only represent a subset of factors that may influence employee turnover, while other aspects such as leadership style, organizational culture or work-life balance were not included.

Future research could address these limitations by applying the analysis to larger and more diverse datasets or by conducting industry-specific studies to examine differences across sectors. Further studies could also integrate additional variables related to organizational culture, leadership, or employee engagement to obtain a more comprehensive understanding of turnover behavior. From a methodological perspective, future research could apply more advanced techniques, such as decision trees or logistic regression that includes feature importance, to identify the exact factors that predict turnover and the weight of each variable. Practical solutions for organizations could include user-friendly interfaces that require no programming skills, allowing human resources teams to upload internal data. Behind the scenes, artificial intelligence could then generate the clusters and provide specific, actionable recommendations for each employee segment, providing important insights to management teams.

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