

THE IMPACT OF MOTIVATIONAL FACTORS ON EMPLOYEE RETENTION IN THE DIGITAL ERA: A PREDICTIVE ANALYSIS BASED ON IBM HR ANALYTICS DATA¹

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Abstract

This study investigates the role of motivational, occupational, and demographic factors in employee retention, in the context of increasing workforce mobility and intensifying competition for talent. The research aims to identify and quantify the main risk and protective factors influencing employees' decision to leave the organization, using modern predictive analysis methods. The study employs the IBM HR Analytics Employee Attrition & Performance dataset, a benchmark dataset frequently used in HR Analytics literature, comprising 1,470 observations and 35 variables relevant to organizational behavior.

The methodology combines binary logistic regression and the Random Forest algorithm to evaluate relationships between motivational, occupational, and demographic variables and the probability of voluntary departure. Data were preprocessed and balanced to correct class imbalance, and bivariate relationships were analyzed using the Spearman coefficient.

Results indicate that working overtime is associated with a 3.41 times higher probability of departure, while high levels of job involvement and job satisfaction are negatively associated with the probability of voluntary turnover. Additionally, the analysis indicates a non-linear relationship between work-life balance and employee retention, suggesting the presence of an optimal level of organizational flexibility.

The conclusions highlight the need for differentiated, data-driven organizational strategies to reduce staff turnover and strengthen employee retention in contemporary organizations.

Keywords: *employee retention; motivational factors; HR analytics; employee attrition; predictive modeling*

JEL Classification: *M12; C53; J28*

1. Introduction

Accelerated technological transformations and the expansion of hybrid work models have profoundly reconfigured the structure and dynamics of the contemporary labor market. The digitization of organizational processes and increasing professional mobility are associated with a growing strategic focus on retaining skilled human capital, which has become an essential factor for maintaining performance and competitive advantage (Armstrong & Taylor, 2023). Currently, employee retention no longer depends exclusively on salary levels, but on a complex combination of motivational, organizational, and personal factors, among which job satisfaction, development opportunities, and work-life balance occupy a central place (Robbins & Judge, 2019). Furthermore, the expansion of remote work models and hybrid arrangements is associated with both new opportunities for employees and significant challenges related to maintaining professional engagement and preventing occupational burnout (Allen, Golden & Shockley, 2015).

Voluntary staff turnover (employee attrition) represents one of the most costly challenges faced by contemporary organizations, generating direct and indirect financial losses associated with recruiting, training, and integrating new employees (Griffeth, Hom & Gaertner, 2000). In the current organizational environment, characterized by intensifying professional demands, factors such as frequent overtime, distance from the workplace, and operational pressures are associated with professional burnout and increased turnover intention (Bakker & Demerouti, 2017). Nevertheless, anticipating departure behavior remains a considerable methodological challenge, as employees'

decisions are simultaneously influenced by numerous interdependent factors whose interactions cannot be captured through simple analytical approaches.

A significant portion of existing research on employee retention relies on qualitative methods - surveys and interviews - or on traditional statistical models that assume linear relationships between variables (Griffeth, Hom & Gaertner, 2000; Hausknecht, Rodda & Howard, 2009). These approaches present recognized limitations in identifying the complex and non-linear relationships specific to organizational behavior. In this context, integrating psychological theories of motivation with advanced Machine Learning techniques represents a promising direction for identifying predictors of staff turnover and for empirically testing theoretical models in real organizational contexts (Marler & Boudreau, 2017).

Based on these considerations, the main objective of this research is to identify and rank the risk and protective factors that influence voluntary employee departure, using predictive methods applied to a benchmark dataset from the HR Analytics literature. The study aims to empirically validate motivational theories within the HR Analytics paradigm, thereby contributing to the foundation of differentiated organizational strategies for reducing staff turnover in contemporary organizations. To this end, the research employs the IBM HR Analytics Employee Attrition & Performance dataset, a benchmark in the specialized literature, which offers the opportunity for quantitative examination of relationships between motivational, occupational, and demographic factors and employee retention behavior. This article represents a substantially extended version of a preliminary study presented at HERGC 2026 (Săcuiu et al., 2026), expanding the theoretical framework, analytical depth, and discussion of results.

2. Literature Review

Employee motivation represents a central determinant of organizational retention, and the specialized literature identifies two distinct categories of factors with asymmetric effects. According to Herzberg's (1959) two-factor theory, hygiene factors such as remuneration prevent dissatisfaction but do not generate long-term loyalty. In contrast, intrinsic motivational factors, such as job involvement and job satisfaction, are associated with psychological attachment to the organization, a perspective also supported by self-determination theory (Ryan & Deci, 2000; Gagné & Deci, 2005). Chung et al. (2023) empirically confirm this distinction, while Gagné and Deci (2005) theoretically argue that high intrinsic motivation is associated with superior organizational commitment: employees with high levels of intrinsic involvement show a significantly lower probability of voluntary departure. However, Vukonjanski et al. (2018) suggest that the relationship between intrinsic motivation and organizational commitment may be moderated by the economic context, with extrinsic factors potentially prevailing under poor economic conditions.

The Job Demands–Resources (JD-R) model describes the mechanism by which operational stress is associated with voluntary turnover: excessive demands are associated with the depletion of personal resources and occupational burnout (Bakker & Demerouti, 2017). Chung et al. (2023) empirically confirm that working overtime (*OverTime*) is the strongest individual predictor of attrition, with effects two to four times greater than other stressors. Distance from home (*DistanceFromHome*) shows a positive association with attrition, possibly mediated by occupational wear, a relationship rarely visible in traditional statistical models.

Regarding work-life balance (WLB), Jaharuddin and Zainol (2019) and Aman-Ullah et al. (2022) empirically demonstrate a significant negative association between low WLB levels and intention to stay in the organization. However, the relationship is not linear: Stock (2015) demonstrates that chronic under-stimulation is associated with *boreout*, a state of profound demotivation characterized by a crisis of meaning and professional boredom, which in turn is negatively associated with organizational commitment. Therefore, optimal retention is not associated with maximum flexibility, but with a balanced level of professional demand, a conclusion that partially contradicts traditional perspectives that treat WLB exclusively linearly.

Griffeth et al. (2000) and Hausknecht et al. (2009) identify a recognized limitation of existing literature: the predominance of qualitative methods and linear models limits the ability to capture complex interactions between variables. Ensemble algorithms such as Random Forest (Breiman, 2001) overcome these limitations by identifying non-linear relationships, representing a direction explicitly recommended in HR Analytics literature (Marler & Boudreau, 2017) and empirically validated on similar data (Chung et al., 2023). The present study follows this direction, combining logistic regression with Random Forest on the IBM HR Analytics dataset, for the empirical validation of motivational theories and the foundation of data-driven retention strategies.

Based on the theoretical framework presented, the following hypotheses were formulated:

- **H1:** Operational stress factors, particularly *OverTime*, are positively associated with the risk of voluntary departure.
- **H2:** High levels of intrinsic motivation (*Job Involvement*, *Job Satisfaction*) are negatively associated with the probability of voluntary turnover.
- **H3:** The relationship between *Work-Life Balance* and retention is not linear, with a moderate-to-high level being more protective than extreme flexibility.
- **H4:** Demographic (*Age*) and financial (*Monthly Income*) factors constitute the structural basis of the retention decision.

3. Data and Methodology

3.1 Dataset Description and Preprocessing

The study employs the IBM HR Analytics Employee Attrition & Performance dataset, a synthetic benchmark dataset frequently used in HR Analytics literature for demonstrative and methodological purposes (Chung et al., 2023; Marler & Boudreau, 2017), comprising 1,470 observations and 35 variables relevant to the analysis of organizational behavior. Data preprocessing and analysis were performed in the R programming environment using the RStudio platform. The dependent variable was defined in binary form through the *Attrition* variable (*Yes* = the employee left the organization; *No* = the employee remained).

In the data cleaning stage, four variables with zero variance or reduced discriminatory capacity were eliminated from the analysis: *Over18*, *EmployeeCount*, *StandardHours* - variables with a unique value for all employees - and *PerformanceRating*, whose distribution, extremely concentrated in two adjacent values (3 and 4), makes it practically non-discriminatory with respect to the target variable. Relevant ordinal categorical variables (*JobSatisfaction*, *WorkLifeBalance*, *JobInvolvement*, *EnvironmentSatisfaction*) were converted to ordered factors to preserve their ordinal structure within the statistical models. Following preprocessing, the final dataset included 31 valid variables.

3.2 Class Imbalance Treatment and Data Division

Exploratory analysis revealed a significant class imbalance in the target variable: 83.88% (n = 1,233) of employees remained in the organization, while 16.12% (n = 237) left. Predictive models trained on imbalanced datasets tend to favor the majority class, which is associated with biased performance estimates and difficulties in correctly identifying departure cases, a recognized methodological issue in Machine Learning applied in HR (Kuhn & Johnson, 2013). To correct this limitation, data were randomly divided into a training set (70%) and a testing set (30%).

A hybrid balancing technique was applied to the training set, combining random undersampling of the majority class (*No*) with oversampling through random duplication of the minority class (*Yes*), using the *downSample()* and *upSample()* functions from the *caret* package in R. The testing set was retained in its original imbalanced form to allow realistic evaluation of the predictive models' generalization capacity.

3.3 Correlation Analysis

To evaluate the bivariate relationships between the independent variables and the target variable (*Attrition*), the Spearman rank correlation coefficient was used. The choice of this non-

parametric method was justified by the ordinal nature of the analyzed variables, such as *JobSatisfaction*, *JobInvolvement*, and *WorkLifeBalance*, which do not satisfy the normality assumption required for applying the Pearson coefficient (Spearman, 1904; James et al., 2021). The correlation analysis provided insight into the direction and intensity of initial relationships between organizational, motivational, and demographic variables and the probability of voluntary departure.

3.4 Binary Logistic Regression

To quantify the effect associated with each predictor on the probability of voluntary departure, a binary logistic regression model was built, a method appropriate for modeling binary dependent variables and widely used in attrition studies (Hosmer, Lemeshow & Sturdivant, 2013). Multicollinearity among predictors was verified by calculating the Variance Inflation Factor (VIF), with all obtained values below the threshold of 2.0, indicating predictor independence and model validity. Model performance was evaluated by estimating the Odds Ratio (OR) with 95% confidence intervals, and the overall predictive capacity was validated through ROC curve analysis and calculation of the area under the curve (AUC), according to the methodology described by Fawcett (2006).

3.5 Random Forest Modeling

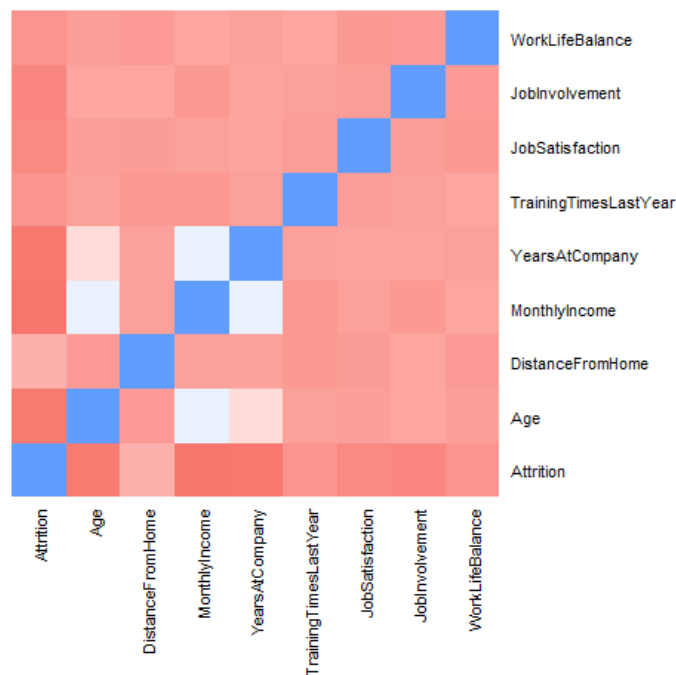
To identify non-linear relationships between variables and complement the parametric analysis, the ensemble-type Random Forest algorithm was implemented, a method that aggregates predictions from a large number of independent decision trees, reducing variance and increasing result robustness (Breiman, 2001). In the modeling process, financially redundant variables (*DailyRate*, *HourlyRate*, *MonthlyRate*) and the unique identifier (*EmployeeNumber*) were excluded, as they represent alternative pay rates with overlapping informational content relative to *MonthlyIncome*, and *EmployeeNumber* is an arbitrary identifier with no organizational significance.

The model was configured with 500 decision trees, and the *mtry* parameter was optimized by minimizing the Out-of-Bag (OOB) error, an internal cross-validation method specific to the Random Forest algorithm (James et al., 2021). Predictor importance was determined using the *Mean Decrease in Gini* metric, which quantifies the contribution of each variable to reducing node impurity and, by extension, to the model's discriminatory power (Breiman, 2001).

4. Results and Discussion

4.1 Bivariate Correlation Analysis and Intrinsic Motivation

The first stage of the analysis sought to identify bivariate relationships between the independent variables and the attrition phenomenon. For this purpose, the Spearman correlation coefficient was used, and the results are represented in (fig. nr. 1) as a heatmap matrix, providing a visual perspective on the intensity and direction of associations between the analyzed variables.

Spearman Correlation Matrix (Balanced Palette)**Figure no. 1. Spearman Correlation Heatmap of Employee Motivation and Retention Factors**

Source: Authors' processing in RStudio based on IBM HR Analytics Dataset

The heatmap reveals consistent negative associations between intrinsic motivational factors, particularly *JobInvolvement* and *JobSatisfaction*, and the probability of voluntary departure, results consistent with the role of psychological commitment as a factor associated with organizational retention. These results are consistent with the theoretical perspective of Gagné and Deci (2005) regarding the role of intrinsic motivation in organizational commitment and with the empirical findings of Chung et al. (2023), who confirm that high intrinsic motivation is negatively associated with the propensity for voluntary departure.

Additionally, the analysis indicates a positive association between *DistanceFromHome* and *Attrition*, suggesting a possible association between long commute distances and occupational wear, a result consistent with the JD-R model (Bakker & Demerouti, 2017). In the context of expanding hybrid work models, this result supports the need for organizational policies oriented toward remote work, which can be associated with reducing occupational wear generated by commuting, according to the literature on telecommuting effectiveness (Allen, Golden & Shockley, 2015).

4.2 Risk and Protective Factors through Logistic Regression

To isolate the specific effect of each predictor on the probability of voluntary departure, a binary logistic regression model was estimated on the balanced dataset. The results, expressed through Odds Ratios (OR) and 95% confidence intervals, allow clear ranking of the risk and protective factors associated with the attrition phenomenon, according to the methodology described by Hosmer, Lemeshow, and Sturdivant (2013).

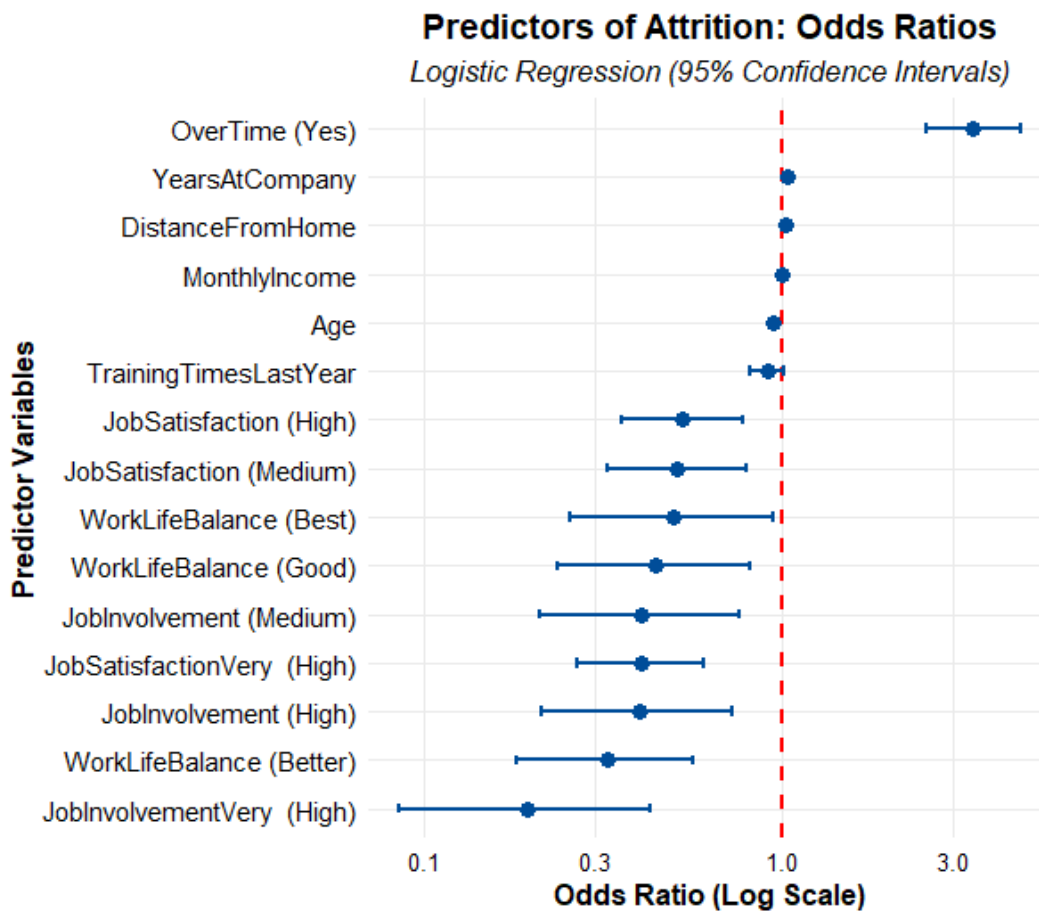


Figure no. 2. Predictors of Attrition: Odds Ratio Analysis (95% CI)
Source: Authors' processing in RStudio based on IBM HR Analytics Dataset

The model reveals that working overtime (*OverTime*) represents the strongest risk factor: employees who work overtime are associated with a 3.41 times higher probability of departure compared to those who do not work overtime (OR = 3.41; 95% CI: 2.53–4.62). This result empirically confirms the predictions of the JD-R model (Bakker & Demerouti, 2017) and is consistent with the literature on the role of chronic operational stress in voluntary turnover.

In contrast, intrinsic motivational factors are negatively associated with the probability of voluntary departure. A very high level of job involvement (*JobInvolvement Very High*) is associated with an odds ratio of 0.194 (OR = 0.194), and very high job satisfaction corresponds to an OR = 0.405, both indicating a significant negative association with the probability of turnover. These results are consistent with the perspective of Ryan and Deci (2000) and Gagné and Deci (2005), according to which intrinsic motivation and psychological commitment to the professional role are positively associated with long-term retention.

Additionally, the results indicate a non-linear relationship between work-life balance and retention, confirming hypothesis H3. The *WorkLifeBalance Better* category is associated with a stronger protective effect (OR = 0.325) than the maximum *Best* level (OR = 0.500), suggesting that optimal retention does not correspond to absolute flexibility, but to a functional level of balance between professional demands and personal resources. This finding is consistent with the excessive flexibility paradox described by Stock (2015) and partially contradicts traditional perspectives that treat WLB exclusively linearly.

4.3 Predictive Capacity Validation of the Model

To evaluate the robustness and generalization capacity of the logistic regression model, its performance was tested on the test sample through ROC (Receiver Operating Characteristic) curve analysis. This method allows assessment of the model's capacity to differentiate between employees

who leave the organization and those who remain, regardless of the chosen classification threshold (Fawcett, 2006).

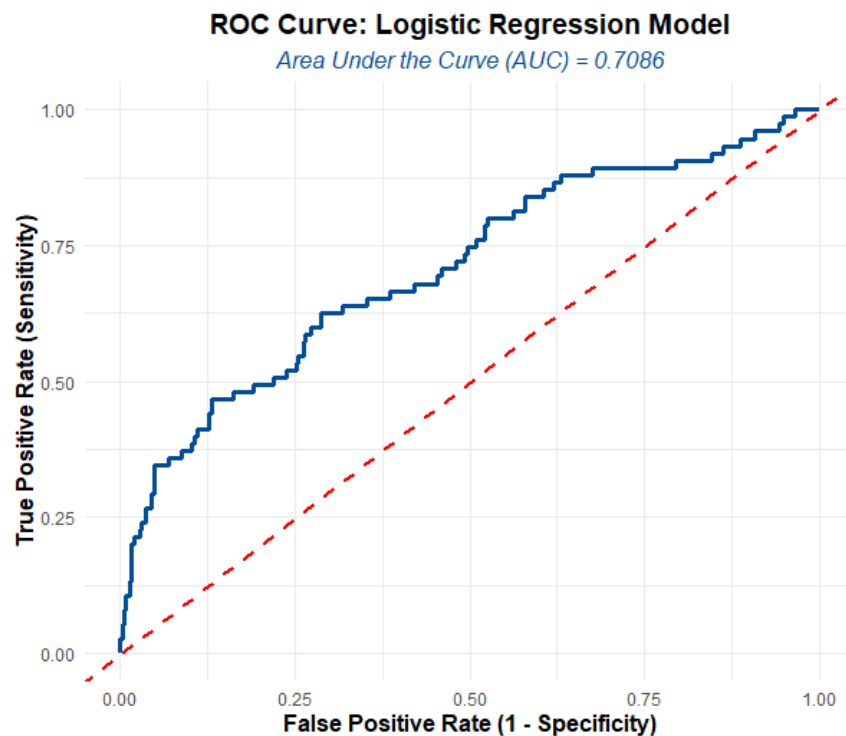


Figure no. 3. ROC Curve for the Balanced Logistic Regression Model

Source: Authors' processing in RStudio

The area under the curve value ($AUC = 0.7086$) indicates acceptable discriminatory capacity. In the specialized literature, AUC values between 0.70 and 0.80 are considered satisfactory for models applied to behavioral and organizational data, where human variability naturally limits the predictive power of any model (Hosmer, Lemeshow & Sturdivant, 2013). The result confirms the predictive validity of the model and the relevance of the motivational, occupational, and demographic variables included in explaining the attrition phenomenon, providing a basis for comparative interpretation of the results obtained through the Random Forest algorithm in the following section.

4.4 Variable Importance Hierarchy in the Random Forest Model

To complement the parametric analysis and capture non-linear relationships between predictors, the Random Forest algorithm was used, and variable importance was evaluated using the *Mean Decrease in Gini* metric (Breiman, 2001). This approach provides a synthetic perspective on the factors that contribute most to differentiating between employees who leave the organization and those who remain, independent of the linearity assumptions specific to logistic regression.

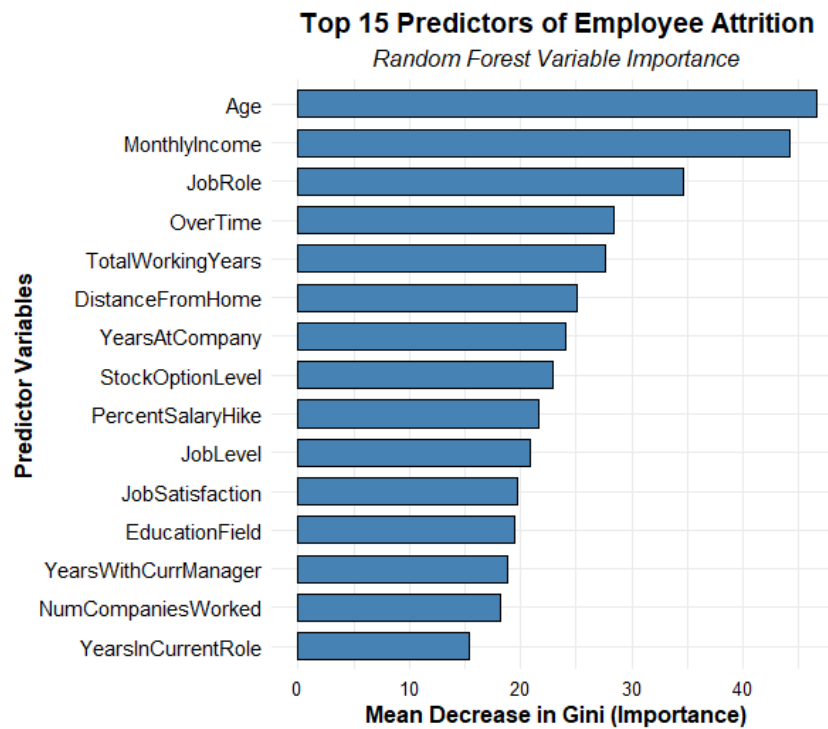


Figure no. 4. Random Forest Variable Importance Ranking (Top 15)

Source: Authors' processing in RStudio based on IBM HR Analytics Dataset

Results indicate that *Age* and *MonthlyIncome* occupy the top positions in the predictor hierarchy, suggesting that career stage and financial stability are structurally associated with the retention decision, a result consistent with the role of financial factors in the specialized literature (Chung et al., 2023).

The presence of *OverTime* among the central predictors confirms, from a non-linear perspective, the association between operational stress and voluntary departure, consolidating the results obtained through logistic regression ($OR = 3.41$) and supporting hypothesis H1.

The high importance of the *JobRole* variable indicates that turnover risk is not uniformly distributed at the organizational level, but varies significantly according to the specifics of the professional role, a result with direct practical implications that supports the need for differentiated retention strategies by occupational categories. Furthermore, the presence of the variables *TotalWorkingYears*, *YearsAtCompany*, and *YearsWithCurrManager* in the top 15 hierarchy suggests that the stability of professional relationships and organizational tenure are negatively associated with the probability of departure, suggesting an organizational anchoring effect - a dimension insufficiently explored in traditional qualitative models.

Taken together, the results of the two models - logistic regression and Random Forest - provide a complementary and robust picture of the factors associated with attrition, empirically validating hypotheses H1–H4 formulated in the previous chapter.

5. Conclusions

The present study sought to identify and quantify the factors associated with voluntary staff turnover, responding to the need to transcend the unidimensional explanatory models predominant in the specialized literature (Griffeth et al., 2000; Hausknecht et al., 2009). By integrating logistic regression and the Random Forest algorithm, the research allowed the empirical validation of relevant theoretical perspectives from human resource management and highlighted the multidimensional nature of employee retention.

The results confirm, in accordance with the Job Demands–Resources model (Bakker & Demerouti, 2017), that excessive professional demands, particularly working overtime, are

associated with the highest probability of voluntary departure (OR = 3.41; 95% CI: 2.53–4.62), supporting hypothesis H1.

At the same time, the analysis indicates that monthly income is associated with the structural basis of the retention decision, in accordance with Herzberg's (1959) two-factor theory, while job involvement and job satisfaction are negatively associated with the probability of voluntary departure, results consistent with self-determination theory (Ryan & Deci, 2000; Gagné & Deci, 2005), validating hypothesis H2.

A distinctive contribution of the study lies in highlighting the non-linear relationship between Work-Life Balance and retention: the *Better* category proved more protective than the maximum *Best* level (OR = 0.325 versus OR = 0.500), confirming hypothesis H3 and the excessive flexibility paradox described by Stock (2015).

Hypothesis H4 is also confirmed, with *Age* and *MonthlyIncome* occupying the top positions in the Random Forest hierarchy, supporting their structural role in the retention decision (Chung et al., 2023).

From a managerial perspective, the conclusions highlight the need for differentiated retention strategies by occupational categories. Limiting overtime, adopting hybrid work models - associated in the literature with reducing occupational wear (Allen, Golden & Shockley, 2015) - and adapting retention interventions according to professional role represent essential practical directions for reducing staff turnover in contemporary organizations.

Nevertheless, the study presents certain limitations that must be acknowledged. The cross-sectional nature of the dataset restricts the possibility of formulating firm causal conclusions, and the generalist nature of the IBM HR Analytics dataset, created for demonstrative purposes, limits the complete transferability of results to specific sectoral contexts (Marler & Boudreau, 2017).

Future research could extend the analysis by using longitudinal datasets and samples from distinct industries, to more precisely capture the influence of organizational and economic particularities on employee retention.

(¹ A preliminary version of this study was presented at the International Scientific Symposium "Horizons of Economic Research in a Global Context" HERGC, 16 May 2026, Târgu Jiu, Romania, and published in the conference proceedings, pp. 176-179, ISSN 3153-2179.)

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