Workplace dynamics and attrition: A logistic regression approach to understanding employee retention

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ABSTRACT

Employee attrition constitutes one of the most consequential and operationally costly challenges confronting contemporary organizations, yet its multifactorial determinants remain imperfectly understood in quantitative terms. This study developed and validated a binary logistic regression model to predict the probability of voluntary resignation among employees, drawing on a secondary dataset of 1,470 employee records obtained from the IBM HR Analytics Employee Attrition dataset via Kaggle. Following point-biserial correlation screening, 19 variables were retained from an initial pool of 35 as significant predictors of attrition. The fitted model demonstrated strong overall performance, achieving 89.0% overall classification accuracy, correctly identifying 97.3% of non-resigning employees, and 46.0% of those who resigned ($\chi^2(41) = 437$, $p < 0.001$; Nagelkerke $R^2 = 0.438$). Twelve variables emerged as statistically significant predictors of attrition at the 0.05 level. Overtime work produced the largest positive effect on resignation odds (OR = 7.27, $p < 0.001$), followed by frequent business travel (OR = 6.52, $p < 0.001$). Among retention-associated predictors, high job involvement (OR = 0.117 at level 4, $p < 0.001$), strong environment satisfaction (OR = 0.269 at level 4, $p < 0.001$), and high job satisfaction (OR = 0.281 at level 4, $p < 0.001$) were most protective against attrition. Additional significant predictors included distance from home, training frequency, tenure in current role, marital status, job role, relationship satisfaction, and work-life balance. These findings provide an empirically grounded predictive framework for HR practitioners and organizational decision-makers seeking to design targeted, evidence-based retention strategies.

1. Introduction

Employee attrition—the voluntary departure of personnel from an organization—represents one of the most economically significant and organizationally disruptive challenges that HR management must navigate. The direct costs of replacing a departing employee, including recruitment, selection, onboarding, and the productivity deficit during the transition period, are estimated to range from 50% to more than 200% of the departing employee's annual salary, depending on seniority and specialization (McConnell, 2011; Scott, Waite, & Reede, 2021). Beyond these direct financial impacts, attrition erodes institutional knowledge, disrupts team cohesion, imposes cultural costs that are difficult to quantify, and can initiate contagion effects in which one departure elevates the resignation intentions of remaining colleagues (Singh, 2019; Das & Baruah, 2013). In sectors where specialized expertise is particularly difficult to replace—healthcare being the paradigmatic case—the consequences are especially acute: physician burnout-related turnover alone is estimated to cost the United States healthcare system $4.6 billion annually (Han et al., 2019).

Notwithstanding the well-established economic significance of attrition, the organizational response has historically been reactive rather than proactive. HR departments have tended to address turnover after it has occurred rather than identifying at-risk employees before they reach the resignation decision. The growing availability of organizational microdata and the concurrent development of accessible machine learning and statistical modelling tools have created a structural opportunity to shift this paradigm: from retrospective analysis of why employees left to prospective identification of who is most likely to leave, and under what organizational conditions. This shift—from descriptive to predictive HR analytics—has gained substantial momentum in both academic and practitioner literatures over the past decade (Mishra, Lama, & Pal, 2016; Zhang et al., 2018).

Logistic regression occupies a particularly important position in this analytical landscape. While more complex machine learning approaches—including random forests, gradient boosting, and neural networks—can achieve higher classification accuracy on held-out test sets, logistic regression offers a combination of statistical interpretability, coefficient-level significance testing, and odds ratio estimation that is essential for translating predictive findings into actionable HR policy. An organization that knows only that a model correctly classifies 92% of employees gains limited operational value; an organization that knows that each unit increase in business travel frequency multiplies resignation odds by a factor of 6.5 gains directly actionable intelligence that can inform travel policy, workload distribution, and compensation design. This interpretive advantage of logistic regression makes it particularly well-suited for the organizational application context that motivates the present study.

The present study develops a binary logistic regression model of employee attrition using the IBM HR Analytics Employee Attrition dataset, a widely used benchmark dataset containing records for 1,470 employees across 35 variables covering demographic characteristics, job attributes, compensation, and satisfaction dimensions. The study addresses a focused set of research questions: Which variables, from among a broad initial predictor set, demonstrate statistically significant associations with voluntary attrition? What is the magnitude and direction of each predictor's effect, as quantified by odds ratios? And what practical interventions do these findings suggest for organizations seeking to reduce avoidable turnover? By providing a systematic, quantitatively rigorous analysis of this dataset, the study contributes both to the academic literature on HR predictive analytics and to the practitioner literature on evidence-based retention strategy design.

2. Literature Review

The academic literature on employee attrition draws from multiple theoretical traditions—organizational behavior, human resource management, labor economics, and industrial-organizational psychology—and is characterized by a long-standing tension between theoretical completeness and practical parsimony. This review synthesizes evidence across four thematic domains particularly relevant to the present study: the organizational and economic consequences of attrition; the principal predictor domains identified in prior empirical research; methodological approaches to predictive attrition modelling; and the specific predictor variables examined in the present analysis.

2.1 ***Organizational and Economic Consequences of Employee Attrition***

The organizational consequences of employee attrition are both direct and diffuse. Direct costs—encompassing position advertising, applicant screening, interviewing, pre-employment testing, and the productivity losses associated with vacancy periods—are well-documented and substantial. McConnell (2011) estimated that turnover costs for frontline health care employees typically range from 75% to 125% of annual salary, with the proportion rising steeply for clinical specialists and senior managers. Scott, Waite, and Reede (2021) extended this analysis to radiology, demonstrating that voluntary turnover carries both quantifiable replacement costs and less-easily-measured institutional knowledge costs as experienced practitioners exit with accumulated technical and contextual expertise. Han et al. (2019), in their comprehensive analysis of physician burnout-related turnover, documented that the annual cost to U.S. healthcare institutions attributable to burnout-driven attrition exceeds $4.6 billion—a figure that, as the authors note, represents only the most directly attributable fraction of the broader systemic costs.

Beyond the direct replacement costs, Wu and Li (2011) analysed the strategic-level consequences of attrition, demonstrating that continuous staff turnover erodes organizational learning capital, disrupts knowledge-transfer processes, and can undermine competitive positioning in industries where human capital is the primary source of differentiation. Anjum et al. (2018) similarly argued that chronic attrition in talent-intensive industries can suppress long-term economic growth by limiting an organization's capacity to accumulate the specialized human capital necessary for sustained innovation. These macro-level consequences underscore why attrition prediction is not merely a personnel administration concern but a strategic management issue with direct implications for organizational performance trajectories.

2.2 ***Key Predictor Domains in the Attrition Literature***

Research on the antecedents of employee turnover intentions and actual attrition has converged, across decades of study, on a set of consistently identified predictor domains. These can be organized into four broad categories: job-intrinsic factors, work environment and relational factors, compensation and structural factors, and individual and demographic characteristics.

Job-intrinsic factors encompass job satisfaction, job involvement, and role clarity. The relationship between job satisfaction and turnover intention is among the most replicated findings in organizational behavior research; Rai et al. (2018) demonstrated that recognition-based satisfaction enhancement significantly reduced voluntary resignation intentions among a diverse employee sample, with employee engagement mediating the relationship between recognition practices and retention outcomes. Job involvement—the degree to which an employee identifies with and is engaged by their work role—has been repeatedly identified as a protective factor against resignation, with highly involved employees demonstrating substantially lower attrition propensity (Misra, Jain, & Sood, 2013).

Work environment and relational factors constitute a second well-evidenced predictor domain. Qian et al. (2023) demonstrated that the quality of workplace social climate, including the prevalence of negative gossip and interpersonal conflict, significantly predicted counterproductive work behaviors and disengagement—precursors to voluntary attrition. Tran et al. (2018) provided direct evidence that high-quality workplace relationships between nurses and their colleagues and supervisors were independently associated with improved job performance and reduced intention to leave, operating through mechanisms of psychological safety, social support, and organizational identification. Meirinhos, Abrunhosa, and Martins (2018) synthesized this evidence in a broader conceptual framework, positioning supportive leadership, positive work culture, and growth opportunities as the three most consequential retention-enabling conditions.

Compensation, structural, and workload factors constitute a third predictor domain with well-established empirical grounding. Steinmetz, de Vries, and Tijdens (2014) demonstrated in a health workforce study that working time—particularly extended overtime—was a more powerful predictor of attrition than wage level, suggesting that workload management may be a higher-priority retention lever than compensation adjustment for many employee segments. Shockley, Smith, and Knudsen (2017) provided an extensive review of the work-life balance literature as it relates to retention, concluding that employees who perceive an irreconcilable conflict between work demands and personal life obligations are at substantially elevated attrition risk, and that flexible work arrangement policies can meaningfully attenuate this risk. Business travel frequency, though less commonly studied as an attrition predictor, has been identified as a compounding stressor: Rundle (2018) documented the health, psychological, and relational costs of frequent business travel, all of which plausibly mediate the travel-to-attrition pathway.

Individual and demographic characteristics represent a fourth predictor domain whose empirical effects are more heterogeneous. Pandey, Singh, and Pathak (2016) found that tenure in the current role—a proxy for role familiarity, social embeddedness, and accumulated role-specific capital—was negatively associated with attrition propensity in retail settings, consistent with March and Simon's (1958) classic proposition that the perceived costs of leaving increase with organizational and role tenure. Terera and Ngirande (2014) identified marital status as a moderator of attrition decisions, with single employees demonstrating higher mobility propensity—a finding interpreted in terms of differential dependency obligations and social anchoring mechanisms. Klotz and Zimmerman (2015) examined role type as an attrition predictor, demonstrating that the demands, visibility, and advancement opportunities associated with different organizational roles interact with individual preferences and external market conditions to produce role-specific attrition patterns.

*2.3 **Predictive Modelling Approaches in HR Analytics***

The application of statistical and machine learning methods to attrition prediction has expanded rapidly since the early 2010s, driven by the increasing digitization of HR data and the growing sophistication of the analytics tools available to practitioners. Zhang et al. (2018) employed machine learning algorithms—including decision trees, random forests, and neural networks—to predict employee turnover characteristics from an IBM HR dataset, demonstrating that ensemble methods could achieve classification accuracy exceeding 85% on held-out validation sets. Mishra, Lama, and Pal (2016) provided a broader conceptual framework for Human Resource Predictive Analytics (HRPA), arguing that predictive HR modelling creates value not through its black-box predictive accuracy alone but through its capacity to identify the organizational conditions and intervention points that meaningfully alter attrition risk.

Binary logistic regression has maintained its position as a methodologically preferred approach for attrition modelling in contexts where interpretability and coefficient-level inference are prioritized alongside predictive performance. Unlike tree-based and neural network approaches, which produce predictions without readily interpretable coefficient estimates, logistic regression yields odds ratios for each predictor that directly quantify the magnitude and direction of the predictor's association with attrition probability, conditional on all other variables in the model. This interpretive transparency is not merely a theoretical nicety; it is a practical requirement for translating predictive findings into organizational interventions. A model that identifies distance from home as a significant predictor—with each additional mile increasing resignation odds by a factor of 1.05—provides operational guidance that a black-box classifier cannot. Hauer, Quan, and Liang (2021) reinforced the value of interpretable predictive frameworks in their analysis of leadership-related attrition in East Asian multinationals, demonstrating that analytically grounded, causally articulate retention frameworks are more readily adopted by organizational decision-makers than opaque algorithmic outputs.

The IBM HR Analytics Employee Attrition dataset used in the present study has become a widely referenced benchmark in the HR predictive analytics literature. Its 35 variables spanning demographic, job-structural, compensation, and satisfaction dimensions provide a rich analytical environment, and its deliberate design to reflect realistic organizational data characteristics—including class imbalance, where non-attriting employees substantially outnumber those who resigned—makes it a valuable testbed for predictive modelling methodologies. Ivana (2020) examined this dataset in a human resource practices context, highlighting the interplay between satisfaction dimensions and structural job characteristics as determinants of retention, while Rekha and Kamalanabhan (2010) contributed complementary evidence from the ITES/BPO sector on the organizational antecedents of turnover in high-pressure, high-attrition work environments.

3. Methodology

3.1 ***Data***

This study utilized the IBM HR Analytics Employee Attrition dataset, a publicly available secondary dataset accessed via Kaggle. The dataset contains records for 1,470 employees across 35 variables, encompassing demographic characteristics (age, gender, marital status, distance from home), job-structural attributes (job level, job role, years at company, years in current role), compensation dimensions (daily rate, hourly rate, stock option level), and attitudinal/satisfaction measures (environment satisfaction, job satisfaction, relationship satisfaction, job involvement, work-life balance). The dependent variable, employee attrition, is a binary variable coded 1 for employees who resigned and 0 for those who remained with the organization. Of the 1,470 employees in the dataset, 237 (16.1%) experienced attrition, reflecting the class imbalance typical of real-world organizational datasets.

To identify the subset of variables with sufficient association with the dependent variable to warrant inclusion in the regression model, point-biserial correlations were computed between each continuous predictor and the binary attrition outcome, and Spearman rank correlations were computed for ordinal predictors. Variables demonstrating statistically significant correlations at the 0.05 level were retained for regression analysis. This screening procedure reduced the active predictor set from 35 to 19 variables. Table 1 presents the description, measurement level, and coding scheme for each retained variable.

Table 1. *Description, Data Type, and Coding of Variables Retained in the Analysis*

Variable	Data Type	Description	Coding
Age	Continuous	Age of the employee in years	—
Attrition	Binary	Whether the employee voluntarily left the organization	Yes = 1; No = 0
Business Travel	Ordinal	Frequency of work-related travel	Non-Travel = 0; Travel Rarely = 1; Travel Frequently = 2
Daily Rate	Continuous	Daily rate of pay (USD)	—
Distance From Home	Continuous	Distance from home to workplace in miles	—
Environment Satisfaction	Ordinal	Satisfaction with the physical and social work environment	1 (Low) to 4 (Very High)
Job Involvement	Ordinal	Degree of psychological engagement with the job role	1 (Low) to 4 (Very High)
Job Level	Ordinal	Hierarchical job level within the organization	1 (Entry) to 5 (Executive)
Job Role	Nominal	Employee's functional role	1 = Healthcare Rep.; 2 = HR; 3 = Lab Technician; 4 = Manager; 5 = Manufacturing Director; 6 = Research Director; 7 = Research Scientist; 8 = Sales Executive; 9 = Sales Rep.
Job Satisfaction	Ordinal	Satisfaction with the job itself	1 (Low) to 4 (Very High)
Marital Status	Nominal	Marital status of the employee	1 = Single; 2 = Married; 3 = Divorced
Overtime	Binary	Whether the employee regularly works overtime	Yes = 1; No = 0
Relationship Satisfaction	Ordinal	Satisfaction with workplace relationships	1 (Low) to 4 (Very High)
Stock Option Level	Ordinal	Stock option allocation level	0 (None) to 3 (High)
Total Working Years	Continuous	Total years of professional employment	—
Training Times Last Year	Continuous	Number of training sessions attended in the preceding year	—
Work-Life Balance	Ordinal	Perceived work-life balance	1 (Bad) to 4 (Best)
Years at Company	Continuous	Years of tenure with the current organization	—
Years in Current Role	Continuous	Years spent in the current job role	—
Hourly Rate	Continuous	Hourly rate of pay (USD)	—

3.2 *Analytical Approach*

Binary logistic regression was employed as the primary analytical method, modelling the log-odds of attrition (coded 1 = resigned, 0 = retained) as a linear combination of the 19 retained predictor variables. Logistic regression was selected for its combination of predictive utility and statistical interpretability: the exponentiated regression coefficients yield odds ratios that directly quantify each predictor's multiplicative effect on attrition odds, conditional on all other variables in the model—a property that is essential for translating statistical findings into actionable organizational interventions. Categorical predictors were effect-coded with reference categories specified a priori: for Business Travel, the Non-Travel category served as reference; for Environment Satisfaction, Job Involvement, Job Satisfaction, Relationship Satisfaction, and Work-Life Balance, Level 1 (lowest satisfaction/involvement) served as reference; for Job Role, Healthcare Representative (code 1) served as reference; for Marital Status, Single (code 1) served as reference; for Overtime, No (code 0) served as reference; and for Job Level, Level 1 served as reference.

On the other hand, model fit was assessed using the chi-square likelihood ratio test, McFadden's R^2 (R^2McF), Cox and Snell R^2 (R^2CS), and Nagelkerke R^2 (R^2N). Classification performance was evaluated using the overall accuracy rate, sensitivity (correct identification of actual employees who resigned), and specificity (correct identification of retained employees). All analyses were conducted in JAMOVI version 2.4.11 using the logistic regression module.

4. Results and Discussion

4.1. *Results*

4.1.1. *Model Fit and Classification Performance*

The binary logistic regression model incorporating all 19 predictors was statistically significant, $\chi^2(41) = 437$, $p < 0.001$, indicating that the full model provided a significantly better fit to the data than a null model predicting attrition from the base rate alone. Model fit statistics indicated adequate explanatory power: $R^2McF = 0.336$, $R^2CS = 0.257$, and $R^2N = 0.438$. The Nagelkerke R^2, commonly interpreted as the approximate proportion of variance in the dependent variable explained by the predictors, indicated that the model accounted for approximately 43.8% of the variance in attrition outcomes—a substantial proportion for a complex behavioral outcome of this type.Table 2 presents the classification table.

Table 2. *Classification Table: Predicted vs. Observed Attrition Outcomes*

Observed		Predicted No	Predicted Yes	% Correct
Employee Attrition	No	1200	33	97.3
	Yes	128	109	46.0
Overall Percentage				89.0

Note. Classification threshold = 0.50. Overall N = 1,470.

As seen in Table 2, the model achieved an overall classification accuracy of 89.0%. Specificity was high (97.3%), indicating that the model was highly effective at identifying employees who would remain with the organization. Sensitivity—the rate at which the model correctly identified actual resigners—was 46.0%, a figure that reflects the well-known challenge of predicting the minority class in imbalanced attrition datasets, where the proportion of actual departures (16.1% in this dataset) creates a structural disadvantage for sensitivity at standard 0.5 probability thresholds.

*4.1.2. **Significant Predictors of Employee Attrition***

Table 3 presents the full binary logistic regression output. Of the 19 predictor variables (generating 41 degrees of freedom after expansion of categorical predictors), 12 demonstrated statistically significant effects on attrition probability at the $\alpha = 0.05$ level. These are reported and discussed below, organized by predictor domain.

Table 3. *Classification Table: Predicted vs. Observed Attrition Outcomes*

Predictor	Estimate (B)	SE	z	p	OR
Intercept	3.268	0.974	3.356	< .001	26.27
Age	−0.016	0.013	−1.239	0.215	0.984
Distance From Home	0.047	0.011	4.291	< .001**	1.048
Daily Rate	-3.91×10^{-4}	2.18×10^{-4}	−1.791	0.073	1.000
Hourly Rate	0.001	0.004	0.230	0.818	1.001
Stock Option Level	−0.192	0.151	−1.270	0.204	0.825
Total Working Years	−0.025	0.027	−0.945	0.344	0.975
Training Times Last Year	−0.176	0.072	−2.441	0.015*	0.839
Years at Company	0.035	0.031	1.149	0.250	1.036
Years in Current Role	−0.130	0.047	−2.764	0.006**	0.879
Business Travel (ref: Non-Travel)					
Travel Rarely	1.034	0.388	2.663	0.008**	2.813
Travel Frequently	1.875	0.418	4.488	< .001**	6.523
Environment Satisfaction (ref: Level 1)					
Level 2	−1.021	0.273	−3.739	< .001**	0.360
Level 3	−1.077	0.245	−4.403	< .001**	0.341
Level 4	−1.312	0.253	−5.184	< .001**	0.269
Job Involvement (ref: Level 1)					
Level 2	−1.183	0.349	−3.388	< .001**	0.306
Level 3	−1.474	0.329	−4.479	< .001**	0.229
Level 4	−2.144	0.459	−4.672	< .001**	0.117
Job Level (ref: Level 1)					
Level 2	−1.828	0.433	−4.222	< .001**	0.161
Level 3	−0.657	0.529	−1.242	0.214	0.519
Level 4	−1.418	0.888	−1.596	0.110	0.242
Level 5	0.669	1.189	0.562	0.574	1.952
Job Role (ref: Healthcare Representative)					
Human Resources	0.626	0.627	0.999	0.318	1.870
Laboratory Technician	0.424	0.563	0.752	0.452	1.528
Manager	−1.088	0.970	−1.122	0.262	0.337
Manufacturing Director	0.095	0.531	0.178	0.859	1.099
Research Director	−2.211	1.043	−2.119	0.034*	0.110
Research Scientist	−0.542	0.583	−0.929	0.353	0.582
Sales Executive	1.345	0.427	3.149	0.002**	3.836
Sales Representative	0.956	0.620	1.541	0.123	2.600
Job Satisfaction (ref: Level 1)					

Level 2	−0.584	0.273	−2.140	0.032*	0.557
Level 3	−0.586	0.238	−2.466	0.014*	0.556
Level 4	−1.269	0.255	−4.977	< .001**	0.281
Marital Status (ref: Single)					
Married	−1.097	0.339	−3.232	0.001**	0.334
Divorced	−0.750	0.246	−3.049	0.002**	0.472
Overtime (ref: No)					
Yes	1.984	0.194	10.251	< .001**	7.272
Relationship Satisfaction (ref: Level 1)					
Level 2	−0.717	0.283	−2.533	0.011*	0.488
Level 3	−0.709	0.247	−2.873	0.004**	0.492
Level 4	−0.714	0.250	−2.850	0.004**	0.490
Work-Life Balance (ref: Level 1)					
Level 2	−0.909	0.363	−2.505	0.012*	0.403
Level 3	−1.308	0.339	−3.857	< .001**	0.270
Level 4	−0.770	0.413	−1.862	0.063	0.463

Note. Model fit: $\chi^2(41) = 437$, $p < 0.001$; $R^2_{McF} = 0.336$; $R^2_{CS} = 0.257$; $R^2_N = 0.438$.

4.2. Discussion

The most powerful predictor of voluntary attrition in the model was overtime work, with employees who regularly worked beyond standard hours exhibiting resignation odds more than seven times higher than those who did not (OR = 7.27, p < 0.001). The magnitude of this effect warrants emphasis: it is the largest odds ratio in the full model, substantially exceeding the next-strongest predictor (frequent business travel, OR = 6.52), and it retained statistical significance at the highest threshold tested (p < 0.001), indicating that the relationship is robust across multiple confidence criteria. This finding is consistent with the burnout-attrition mechanism documented by Steinmetz, de Vries, and Tijdens (2014) in the health workforce context—wherein working time extensions produce compounding psychological costs that eventually exceed the individual's capacity to sustain organizational commitment—and aligns with the broader work-life balance literature's consistent identification of unmanageable workload as a primary driver of turnover intention (Shockley et al., 2017). The organizational implication is direct: overtime reduction, redistribution of excess workload across a broader staffing base, and clear policy frameworks that limit unsustainable work-hour demands are likely to yield measurably higher returns in attrition reduction than compensation or satisfaction-focused interventions for employees in overtime-intensive roles.

Business travel frequency also emerged as a strong positive predictor, with a clear dose-response pattern: employees who rarely travel exhibited 2.81 times higher resignation odds than non-travelers (OR = 2.81, p = 0.008), while frequent travelers demonstrated 6.52 times higher odds (OR = 6.52, p < 0.001). This graduated pattern—which was observed across both travel frequency categories in the expected ordinal direction—is theoretically interpretable in terms of the cumulative strain effects of travel on personal routines, family obligations, sleep quality, and self-perceived work-life balance documented by Rundle (2018). The multiplicative increase from rare to frequent travel suggests that organizational travel demands do not merely inconvenience employees but impose costs that compound in a manner disproportionate to travel frequency, perhaps because the unpredictability and loss of personal control associated with frequent travel generate qualitatively different psychological responses from occasional disruption. Practically, this finding supports organizational policies that cap travel obligations, distribute them more equitably across work groups, and aggressively substitute virtual meeting formats for travel that does not require physical presence.

Distance from home produced a modest but statistically robust positive effect on attrition odds (OR = 1.048 per unit mile, $p < 0.001$). While a single-unit increase in commute distance translates to only a 4.8% increase in resignation odds, this effect accumulates meaningfully across the realistic range of commute distances in the dataset: an employee commuting 30 miles farther than a comparator would exhibit approximately 4.06 times higher attrition odds, all else equal. This finding is consistent with Ma and Ye's (2019) demonstration that commute burden significantly impairs employee productivity and contributes to work-life balance deterioration. Remote and hybrid work arrangements, commuter assistance programs, and geographic proximity as a factor in location strategy for new facilities are all organizational responses that this finding supports.

Job involvement demonstrated a strong, monotonically increasing protective effect against attrition across all three contrasting levels. Employees at the second level of involvement exhibited resignation odds 69.4% lower than those at the minimum involvement level (OR = 0.306, $p < 0.001$); by the highest involvement level, this protection intensified to a 88.3% reduction in attrition odds (OR = 0.117, $p < 0.001$). This is one of the strongest protective effects in the full model and aligns closely with Misra, Jain, and Sood's (2013) theoretical account of job involvement as a retention mechanism: highly involved employees derive intrinsic meaning and identity from their work roles, which substantially raises the psychological cost of voluntary departure and simultaneously reduces the comparative attractiveness of alternative employment. The practically important implication is that the organizational levers for increasing job involvement—task enrichment, expanded decision-making authority, visible contribution to organizational purpose, and role design that challenges and develops employees—are likely to produce measurable attrition reductions beyond what compensation adjustments alone can achieve.

The relationship between job satisfaction and attrition followed an expected negative gradient. Employees at the second and third satisfaction levels exhibited comparable attrition odds reductions relative to the lowest satisfaction level (OR = 0.557 and 0.556 respectively, both significant at $p < 0.05$), with the largest protection observed at the highest satisfaction level (OR = 0.281, $p < 0.001$). The convergence of the odds ratios at levels 2 and 3 is a notable pattern: it suggests a nonlinear protective effect in which the attrition-reducing benefit of moving from low to moderate satisfaction is substantial, while a further increment from moderate to moderately-high satisfaction produces relatively little additional protection—with the largest additional benefit arising in the transition to very high satisfaction. This nonlinear pattern has practical implications for resource allocation in satisfaction improvement programs: interventions targeting the most dissatisfied employees are likely to yield the highest per-dollar attrition reduction, while marginal investments to shift already-moderately-satisfied employees toward very high satisfaction may produce incrementally smaller returns until the highest satisfaction levels are reached. Rai et al.'s (2018) finding that recognition-based interventions significantly improve retention through an engagement-mediated pathway suggests that recognition programs targeting low-satisfaction employees may be particularly cost-effective retention investments.

Tenure in the current role exhibited a negative and significant effect on attrition (OR = 0.879 per additional year, p = 0.006), indicating that each year of additional tenure in a given role reduces resignation odds by approximately 12.1%. This finding is theoretically consistent with Pandey, Singh, and Pathak's (2016) evidence that role familiarity and accumulated role-specific social capital reduce attrition propensity—employees in roles they have held for several years have developed efficient work routines, strong collegial relationships, and a clear understanding of their contribution to the organization, all of which constitute costs of departure that recent hires have not yet accumulated. The finding also resonates with March and Simon's (1958) proposition that perceived ease of movement moderates the relationship between job attitudes and actual departure: employees firmly embedded in a current role may perceive greater barriers to departure even when satisfaction is moderate. Practically, this finding reinforces the value of structured role development and career lattice programs that create meaningful advancement opportunities within roles, rather than requiring employees to leave current positions entirely in order to progress.

Training frequency in the preceding year demonstrated a protective negative effect on attrition (OR = 0.839 per additional training occasion, p = 0.015), such that each additional training session attended in the prior year was associated with a 16.1% reduction in resignation odds. This finding carries a straightforward but important organizational message: investment in employee development is not merely a productivity intervention but a retention investment. Zhang et al. (2018) identified training access as a significant attrition predictor in their machine learning analysis of the same dataset, and the present finding quantifies this relationship through an odds ratio that can be directly compared against the cost of providing additional training to at-risk employees. Organizations that systematically under-invest in training—particularly for frontline and mid-career employees who may perceive limited development investment as a signal of low organizational commitment to their professional futures—are plausibly amplifying their attrition risk in ways that more than offset the short-term cost savings from reduced training expenditure.

Environment satisfaction demonstrated a strong, consistent protective effect against attrition across all contrasting levels. The odds ratios decreased monotonically from Level 2 (OR = 0.360) through Level 3 (OR = 0.341) to Level 4 (OR = 0.269), all significant at $p < 0.001$, indicating that any increment in environment satisfaction above the minimum is associated with meaningful attrition reduction, with the protection becoming most pronounced at the highest satisfaction level. This finding extends Qian et al.'s (2023) evidence on the attrition-promoting effects of negative workplace social climate, providing quantitative odds estimates for the protective effect of a positive environment. The practical interventions that environment satisfaction improvements support—inclusive organizational culture development, physical workspace quality, prompt resolution of harassment and incivility, and managerial training in psychological safety practices—are broadly available to organizations and carry well-documented co-benefits in terms of organizational citizenship behavior, knowledge sharing, and team performance that make them defensible investments beyond their attrition-reduction returns.

Relationship satisfaction—reflecting the quality of interpersonal connections with colleagues and supervisors—produced a statistically significant protective effect at all three contrasting satisfaction levels (ORs ranging from 0.488 to 0.490, all $p \leq 0.011$). The convergence of odds ratios across Levels 2, 3, and 4 (0.488, 0.492, and 0.490 respectively) is a theoretically interesting pattern: it suggests that the primary benefit of relationship satisfaction for attrition prevention lies in the transition from low satisfaction to any higher level, with relatively modest incremental benefit from further increments. This pattern may reflect the binary character of the psychological mechanism involved—either employees feel socially supported and connected within their work environment, or they do not—with the fine-grained distinctions between moderate and high relationship quality being less consequential for attrition decisions than the more fundamental question of whether minimal social integration thresholds are met. Tran et al.'s (2018) evidence that high-quality workplace relationships improve nurse performance through psychological safety and social support mechanisms provides a plausible mediating account: it is the presence of psychological safety rather than the precise quality of individual relationships that most directly influences the resignation calculus.

Work-life balance perception produced significant negative effects on attrition at Levels 2 and 3 of the scale (OR = 0.403, $p = 0.012$, and OR = 0.270, $p < 0.001$, respectively), while Level 4 narrowly missed significance (OR = 0.463, $p = 0.063$). The non-significant Level 4 effect is a counterintuitive pattern that warrants interpretive care: one possible explanation is that employees who perceive the highest level of work-life balance are a relatively small and atypically embedded group whose low attrition rate is driven by factors not fully captured by the work-life balance construct itself. Alternatively, the non-significance at Level 4 may reflect power limitations associated with the small number of employees at the highest scale value. Shockley et al.'s (2017) comprehensive review of the work-life balance retention literature consistently identifies flexible work arrangements and workload management as the most potent organizational levers for improving work-life balance perceptions, and the present findings reinforce the relevance of these interventions as attrition management tools.

Among job role comparisons, two significant contrasts emerged relative to the Healthcare Representative reference category. Research Directors exhibited substantially lower attrition odds (OR = 0.110, $p = 0.034$), reflecting a pattern consistent with Klotz and Zimmerman's (2015) evidence that higher-prestige, higher-autonomy roles with clearer advancement pathways and stronger professional identity are associated with reduced resignation propensity. Research directors typically occupy positions characterized by high intellectual engagement, specialized expertise, and organizational indispensability—characteristics that collectively elevate the psychological costs of departure and reduce the perceived attractiveness of external alternatives. Sales Executives, by contrast, demonstrated markedly elevated attrition odds (OR = 3.836, $p = 0.002$), consistent with the broader literature on sales force turnover, which identifies target-pressure stress, customer rejection exposure, and the commission-based employment structures common in sales roles as chronic attrition-promoting conditions. The divergence between these two roles—one with an attrition odds ratio approximately nine times lower than the other—underscores the importance of role-differentiated retention strategies that recognize the qualitatively different attrition risk environments in which different employee segments operate.

For job level, only the Level 2 versus Level 1 contrast reached significance (OR = 0.161, $p < 0.001$), indicating that employees at the second hierarchical level are substantially less likely to resign than entry-level (Level 1) employees, while differences between higher levels and the entry reference did not reach statistical significance. This pattern is consistent with the well-documented phenomenon of first-year and early-career attrition as the highest-risk attrition window, where adjustment challenges, unmet expectations, and limited organizational embeddedness produce elevated resignation rates. Investing proportionately more in onboarding, integration support, and early career development for Level 1 employees is the most directly actionable implication of this finding.

Marital status produced the anticipated pattern: both married and divorced employees exhibited significantly lower attrition odds than single employees (OR = 0.334, $p = 0.001$ and OR = 0.472, $p = 0.002$, respectively). The larger protective effect for married employees relative to divorced employees is consistent with Terera and Ngirande's (2014) evidence that marital dependency obligations and social anchoring mechanisms reduce employment mobility propensity—married employees with dependent spouses or children face higher perceived departure costs, both financial and social, that reduce their propensity to act on turnover intentions even when attitudinal conditions for departure are present. While marital status is not directly actionable as an organizational retention lever, the finding has practical relevance for talent pipeline management: organizations with predominantly young, single workforces face structurally higher attrition baselines than those with more demographically diverse employee populations, a fact that should inform realistic target-setting for retention improvement programs.

5. Conclusion

This study developed a binary logistic regression model of employee attrition using a validated organizational dataset of 1,470 employee records, achieving 89.0% overall classification accuracy and identifying twelve statistically significant predictors spanning workload, job-intrinsic, relational, satisfaction, and demographic domains. The model's most striking finding—that overtime work increases resignation odds more than sevenfold—represents a particularly actionable organizational insight, as overtime management is a directly controllable organizational policy variable whose attrition costs have been systematically underweighted relative to its operational benefits in the organizational management literature. Business travel frequency, distance from home, job involvement, job satisfaction, environment satisfaction, relationship satisfaction, work-life balance, training frequency, role tenure, job role, job level, and marital status round out the predictive model, each contributing complementary and non-redundant information about the conditions under which voluntary departure becomes the employee's preferred option.

Together, these findings build an empirically grounded argument for a retention strategy that is simultaneously multi-dimensional and analytically targeted. Multi-dimensional because the predictors of attrition are irreducibly heterogeneous—no single variable accounts for more than a fraction of the total explained variance, and the most effective interventions will address multiple risk dimensions concurrently. Analytically targeted because the odds ratios for each predictor—and particularly the role-specific and satisfaction-specific contrasts—enable organizations to direct their retention investments toward the conditions and employee segments where the expected attrition reduction per unit of investment is highest, rather than distributing resources uniformly across a workforce in which attrition risk is substantially unequal.

This study is not without limitations. The dataset is cross-sectional and synthetic—constructed by IBM for illustrative purposes rather than drawn from a single real organization—which limits the direct generalizability of the specific coefficient values to any particular organizational context. The model's sensitivity (46.0%) reflects the class imbalance inherent in any attrition dataset and indicates that a meaningful proportion of actual employers who resigned would not be correctly flagged by the model at the standard 0.5 probability threshold; lower thresholds or cost-sensitive classification approaches would improve sensitivity at the expense of specificity. Furthermore, the absence of variables capturing several theoretically important attrition determinants—including supervisor relationship quality, perceived organizational justice, career development satisfaction, and external labor market conditions—limits the model's explanatory completeness and introduces the possibility of omitted variable bias in the coefficient estimates. Future research extending this analysis to primary organizational data from specific industry or regional contexts, incorporating longitudinal designs that can better establish temporal precedence, and systematically comparing logistic regression performance against ensemble and deep learning approaches on matched datasets would substantially advance the predictive HR analytics literature.

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NO CONFLICT OF INTEREST STATEMENT

All authors declare that they have no conflict of interest.

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