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Predicting Employee Attrition: Data-Driven Strategies to Reduce Turnover

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Abstract: Employee attrition remains a significant challenge for organizations seeking to sustain workforce stability, productivity, and long-term growth. While some degree of attrition is inevitable, excessive turnover imposes substantial operational and financial costs, making effective prediction and prevention essential. This study examines the multifaceted drivers of employee attrition and demonstrates how data-driven approaches can support proactive retention strategies. Using a large-scale dataset of 14,900 employees obtained from Kaggle, the study applies logistic regression analysis to identify demographic, job-related, and organizational predictors of attrition. The results reveal that attrition is strongly associated with factors such as job level, tenure, remote work status, promotions, work–life balance, and indicators of career mobility, while compensation alone shows limited explanatory power. The predictive model exhibits strong performance, explaining approximately 46.3% of the variance in attrition and achieving an overall accuracy of 75.1%, with balanced sensitivity and specificity. Notably, employees in senior roles, remote workers, highly educated staff, and high performers were found to be at elevated risk of leaving. The findings challenge conventional assumptions about retention and highlight the importance of leveraging predictive analytics to identify high-risk groups. Overall, the study underscores that employee attrition is both predictable and manageable through targeted, data-informed HR interventions.

Keywords: Attrition, Predictor, Logistic Regression, Multifaceted, Turnover.

I. INTRODUCTION

Employee attrition, sometimes referred to as staff turnover, is the gradual reduction of a company's workforce as employees leave and are not immediately replaced. Attrition has become a critical focus for human resources (HR) leaders seeking to maintain a stable, engaged, and high-performing workforce. 72% of HR professionals consider employee retention to be their top challenge, HR Research Institute (2023). While a certain level of attrition is normal and even healthy, excessive or uncontrolled attrition can become a significant organizational problem. High attrition impacts operational continuity, performance, morale, and the financial health of the business. Understanding the root causes, recognizing the short and long-term effects, and developing sustainable strategies to minimize attrition are essential for organizations aiming for stability, productivity, and long-term growth.

As workplaces become more dynamic and employees demand better experiences, companies are increasingly turning to data-driven approaches to understand, predict, and reduce turnover. This article explores the key causes of attrition, how predictive analytics can help, and strategies organizations can adopt to minimize attrition. The remaining part of the article looks at causes of employee attrition, predicting employee attrition, conclusion and recommendations.

II. CAUSES OF EMPLOYEE ATTRITION

Employee attrition does not occur for a single reason; rather, it results from a variety of organizational, personal, and external factors. Understanding these causes helps companies design interventions that directly address the root issues. Recognizing which employees are likely to leave, and understanding the factors driving their departure is essential for creating effective retention policies and strategies (Alao and Adeyemo, 2013). By analyzing employee data, such as career goals, promotions, recruitment history, age, performance evaluations and training, across multiple dimensions, organizations can identify various drivers of attrition (El-Rayes et al., 2020). Advances in predictive analytics now allow companies to anticipate employee turnover with up to eighty-five percent accuracy by examining indicators like workload, tenure and engagement levels (Anuradha & Rani, 2024). In addition, factors such as insufficient compensation prompting employees to seek better opportunities, declining motivation and morale, and ineffective hiring practices can further elevate attrition rates (Katekhaye & Gahalod, 2024).

One of the most common reasons employees leave is the absence of opportunities for advancement. When employees feel stuck in stagnant roles with no clear path for learning or promotion, they begin seeking growth elsewhere. When employees cannot envision a future within the organization, they often look elsewhere. Stagnation in promotions, skill development, or new opportunities drives attrition. Organizations that fail to provide training, mentorship programs, and pathways for professional mobility often experience higher turnover, especially among high-performing and ambitious employees.

Job satisfaction level of an employee is significantly affected by the compensation practices in the organization (Sokoya 2000), Opkara (2002) and Frye (2004). Salary dissatisfaction remains a major trigger for attrition. Employees compare their wages not only within the organization but also across the industry. When compensation packages; salary, bonuses, allowances, health insurance and retirement plans do not align with market standards or do not reflect the employee's value, they eventually leave for more competitive offers. Additionally, benefits that fail to support work-life balance, such as flexible schedules or wellness programs, can push employees toward companies that prioritize their personal well-being.

The saying "employees don't leave companies; they leave managers" reflects a significant truth. A significant portion of employees cite their manager, not their job, as the main reason for leaving. Ineffective communication, lack of support, and micromanagement can push employees toward the exit. Poor leadership such as micromanagement, lack of communication, favoritism, inadequate feedback, or lack of support creates a toxic work environment. Employees who feel undervalued, disrespected, or unsupported by their supervisors are highly likely to exit the organization.

Organizations that consistently demand excessive workloads, long hours, or unrealistic performance expectations create chronic stress among employees. Over time leads to burnout, decreased morale, and eventually resignation. Work-life imbalance, especially when remote or hybrid work is not available even where feasible, becomes a major driver of voluntary turnover.

Company culture values, norms, behavior patterns and communication style plays a critical role in employee satisfaction. A toxic or misaligned culture characterized by poor communication, discrimination, lack of inclusivity, or absence of teamwork creates frustration and disengagement. Employees who feel isolated, undervalued, or culturally misaligned are more inclined to leave.

Employees want their efforts to be acknowledged. A workplace that rarely recognizes accomplishments, ignores employee input, or fails to reward good performance creates feelings of invisibility and demotivation. Lack of appreciation lowers morale and drives employees to organizations where their contributions are valued. Employees who feel undervalued, underpaid, or unchallenged are more likely to leave. Lack of recognition, unclear expectations, or repetitive tasks often contribute to frustration and disengagement.

Sometimes attrition is driven by favorable external factors, including better job offers from competitors, industry growth creating higher-paying opportunities, geographic relocation and desire for a change in career path. Organizations cannot control these factors entirely but can reduce their impact through strong retention strategies.

When employees are placed in roles that do not match their talents, passions, or expectations, dissatisfaction arises. Mis-hiring, unclear job descriptions, or unrealistic expectations can make employees feel frustrated and ineffective, prompting them to leave.

III. PREDICTING EMPLOYEE ATTRITION

Effective forecasting depends on quality data. Common features used in predictive attrition models include, demographic factors: age, gender, tenure, education level, job-related factors: job role, department, pay grade, promotions, performance ratings, workplace behavior: absenteeism, training hours, engagement scores, Compensation and benefits: salary, variable pay, benefit utilization and Organizational factors: leadership changes, workload, remote vs. on-site status

Organizations may also incorporate qualitative data such as employee surveys or exit interview themes to enrich the model. Logistic regression is one of the traditional techniques that have been applied in the forecasting of employee attrition. Unlike Amand et al. (2023), who dismiss the technique on the grounds that it may not capture the non-linear relationships between employee attrition and its influencing factors, logistic regression is in fact a non-linear modeling method.

Predictive analytics has emerged as a powerful tool for HR teams, enabling them to anticipate turnover before it happens. Rather than reacting to resignations, organizations can take proactive steps using data insights. This section analyses data from Kaggle on attrition. The analyzed dataset had 14900 respondents. Jamovi was used to analyze the data.

A logistic regression analysis was conducted to examine the factors influencing employee attrition, where the dependent variable was coded as 1 for employees who left and 0 for those who stayed. The model included demographic, job-related, and organizational factors.

Table 1

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	6330.110	39	.000
	Block	6330.110	39	.000
	Model	6330.110	39	.000

Table 1 shows the Omnibus Tests which indicate that the model is highly significant, $\chi^2(39) = 6330.110$. Looking at the row marked 'step 1', we see that the p-value is 0.000, suggesting that the model is very significant. This confirms that the full model with demographic, job, and organizational predictors fits the data significantly better than a null model with no predictors.

Table 2 shows the pseudo-R-square

Table 2

Model Fit Measures

Model	Deviance	AIC	R^2_N
1	14256	14340	0.463

The overall model demonstrated a good fit to the data. The model deviance was 14256, with an AIC of 14340. Nagelkerke's pseudo-R^2 was 0.463, indicating that the model explains a substantial proportion of the variation in attrition. In the context of logistic regression, this represents a strong model fit, suggesting that the included predictors meaningfully improve prediction over a null model. Given the large sample size, an AIC of 14340 is relatively low, suggesting a well-balanced model with good explanatory power relative to its complexity.

The Nagelkerke R-square value in table 2 is 0.463. Its meaning is roughly similar to the R-square in the least squares regression model. In this case we may say, roughly 46.3 percent of the variance in employee attrition, which is substantial for behavioral and organizational outcomes, is explained by the model. This indicates strong practical usefulness for human resources decision-making.

Table 3

Classification Table

	Predicted		
Observed	**Left**	**Stayed**	**% Correct**
Left	5153	1879	73.3
Stayed	1784	6084	77.3

Note. The cut-off value is set to 0.5

Table 3 presents the classification results, showing the distribution of employees who stayed or left, by observed outcomes and model predictions. In the table, 6084 of the employees who stayed were predicted to have stayed with the company by the model. Similarly, 5153 of the employees who had left were predicted by the model, to have left. The model demonstrates balanced predictive performance, effectively avoiding the common issue of accurately predicting retention while underperforming on attrition. This balance makes it well suited for early-warning systems and targeted interventions.

Table 4

Predictive Measures

Accuracy	Specificity	Sensitivity
0.751	0.733	0.77.3

Note. The cut-off value is set to 0.5

Table 4 summarizes the model's sensitivity, specificity, and accuracy. Sensitivity (true positive rate) represents the proportion of individuals who left and were correctly predicted to leave, at 76.5%. Specificity (true negative rate) reflects the proportion of individuals who stayed and were correctly predicted to stay, at 73.6%. Overall model accuracy, indicating the percentage of correct predictions, is 75.1%. Such a model would be very good for managers who are keen to minimize attrition.

Table 5

Model Coefficients - Attrition

Predictor	Estimate	SE	Z	p	Odds ratio
Intercept	-5.46422	0.20285	-26.9368	< .001	0.00424
Age	0.00747	0.00201	3.7164	< .001	1.00750
Gender:					
Male – Female	0.56664	0.04182	13.5507	< .001	1.76234
Years at Company	0.01503	0.00239	6.2951	< .001	1.01515
Job Role:					
Finance – Education	0.18076	0.09755	1.8530	0.064	1.19812
Healthcare – Education	0.12517	0.08546	1.4646	0.143	1.13334
Media – Education	0.24532	0.07230	3.3932	< .001	1.27803
Technology – Education	0.20049	0.09841	2.0373	0.042	1.22201
Monthly Income	-1.47e- 5	1.67e-5	-0.8821	0.378	0.99999
Work-Life Balance:					
Excellent – Poor	1.59621	0.07580	21.0585	< .001	4.93429
Fair – Poor	0.25760	0.06721	3.8326	< .001	1.29383
Good – Poor	1.34239	0.06626	20.2583	< .001	3.82819
Job Satisfaction:					
High – Low	0.62361	0.07059	8.8342	< .001	1.86566
Medium – Low	0.52869	0.07953	6.6478	< .001	1.69671
Very High – Low	0.04267	0.07876	0.5417	0.588	1.04359
Performance Rating:					
Average – Low	0.52576	0.09519	5.5231	< .001	1.69175
Below Average – Low	0.18152	0.10609	1.7109	0.087	1.19904
High – Low	0.45256	0.10213	4.4311	< .001	1.57233
Number of Promotions	0.27127	0.02110	12.8541	< .001	1.31163
Overtime:					
Yes – No	-0.35698	0.04403	-8.1071	< .001	0.69979
Distance from Home	-0.00977	7.28e-4	-13.4104	< .001	0.99028
Remote Work:					
Yes – No	1.84626	0.05948	31.0377	< .001	6.33610
Education Level:					
Associate Degree – High School	0.07472	0.06187	1.2078	0.227	0.92800
Bachelor's Degree – High School	0.02661	0.05970	0.4458	0.656	1.02697
Master's Degree – High School	0.01189	0.06518	0.1825	0.855	1.01196
PhD – High School	1.69282	0.11686	14.4856	< .001	5.43478
Marital Status:					
Divorced – Single	1.56678	0.06491	24.1373	< .001	4.79118
Married – Single	1.89222	0.04947	38.2528	< .001	6.63407
Number of Dependents	0.12842	0.01346	9.5423	< .001	1.13703
Job Level:					
Mid – Entry	1.03628	0.04587	22.5901	< .001	2.81872
Senior – Entry	2.70620	0.06590	41.0674	< .001	14.97234
Company Size:					
Large – Small	0.18509	0.05984	3.0929	0.002	1.20332
Medium – Small	0.21230	0.04783	4.4385	< .001	1.23652
Company Tenure	-7.21e- 5	9.12e-4	-0.0791	0.937	0.99993
Leadership Opportunities:					
Yes – No	0.30134	0.09522	3.1647	0.002	1.35166
Innovation Opportunities:					
Yes – No	0.13739	0.05657	2.4286	0.015	1.14728
Company Reputation:					
Excellent – Poor	0.73402	0.08091	9.0721	< .001	2.08345
Fair – Poor	0.16667	0.06520	2.5564	0.011	1.18136
Good – Poor	0.72845	0.05460	13.3410	< .001	2.07186
Employee Recognition:					
High – Low	0.01897	0.05294	0.3582	0.720	1.01915
Medium – Low	0.02413	0.04965	0.4861	0.627	1.02443
Very High – Low	0.04292	0.10014	0.4286	0.668	1.04385

Table 5 presents the regression coefficients, standard errors, Z-values, p-values, and odds ratios for each predictor. The intercept of -5.464 with p-value < .001, represents the log-odds of an employee leaving when all predictors are at their reference levels or zero. Its corresponding odds ratio of 0.004 indicates that in the absence of other factors, the probability of leaving is very low.

Several demographic and experience-related variables were significantly associated with attrition. Age had a small but statistically meaningful effect, with older employees being slightly more likely to leave the organization. Gender differences were pronounced, as male employees exhibited substantially higher odds of attrition compared to female employees. Tenure also mattered: employees with more years at the company were marginally more likely to leave, potentially reflecting greater exposure to external labor market opportunities over time.

Family-related characteristics further shaped attrition risk. Married and divorced employees were significantly more likely to leave than single employees, and attrition odds increased steadily with the number of dependents, suggesting that family responsibilities and financial pressures may influence mobility decisions. Compared to single employees, married employees were more than six times as likely to leave, while divorced employees had nearly five times higher odds of attrition. The is reflected by the odds ratios of 6.63 and 4.79 that are in table 5. Additionally, each additional dependent increased attrition odds by approximately 14% as provided by the odds of 1.14, indicating that greater family responsibilities may heighten mobility pressures.

Indicators of human capital and career advancement emerged as some of the strongest predictors of attrition. Education level was largely unrelated to turnover risk, except for employees holding a PhD. Compared to those with a high school education, PhD holders showed a large and statistically significant effect, regression coefficient of 1.693, with odds of attrition of 5.43.

Job level exhibited a strong gradient. Relative to entry-level employees, mid-level employees were nearly three times as likely to leave, while senior-level employees showed an exceptionally high likelihood of attrition with regression coefficient of 2.706, p-value less than 0.001and odds almost fifteen times greater than the reference group. Similarly, the number of promotions significantly increased attrition risk ($\beta = 0.271$, $p < .001$), reinforcing the idea that upward mobility is associated with greater external employability. Performance ratings followed a comparable pattern, as employees with average and high performance were significantly more likely to leave than low performers.

Attrition also varied across functional roles. Relative to employees in education-related positions, those in media, and technology had significantly higher odds of leaving, representing increases of approximately 28% and 22%, respectively. No statistically significant differences were observed for finance or healthcare roles. Evidence to support this can be obtained from table 5.

Several work experience variables showed notable, and in some cases counterintuitive relationships with attrition. Job satisfaction demonstrated mixed effects: employees reporting medium or high satisfaction were more likely to leave than those with low satisfaction, whereas very high satisfaction was not statistically significant. This pattern may reflect overqualification, unmet expectations, or confidence in securing alternative employment among moderately satisfied employees.

Work and life balance was among the strongest predictors of attrition. Employees reporting excellent balance had nearly five times higher odds of leaving compared to those with poor balance, odds ratio of 4.93, while good balance was associated with roughly four times higher attrition odds. In contrast, overtime work significantly reduced attrition likelihood with a regression coefficient of −0.357, which was significant. Employees working overtime about were 30% less likely to leave, potentially signaling stronger engagement or organizational commitment.

Work structure and location also played important roles. Remote work was a particularly strong predictor of attrition, with remote employees facing more than six times the odds of leaving. Monthly income, however, was not a significant predictor (p-value = 0.378), suggesting that compensation alone may not offset other drivers of turnover.

Geographical factors were related to attrition, with employees living further from the workplace exhibiting a lower likelihood of leaving, potentially reflecting relocation constraints or the presence of sunk commuting costs.

Finally, perceptual variables related to organizational signaling were positively associated with attrition. Employees who perceived greater leadership and innovation opportunities were significantly more likely to leave, potentially reflecting higher ambition or enhanced external marketability. Similarly, employees who rated the company's reputation more positively, particularly those rating it as excellent, exhibited higher attrition odds, consistent with reputational signaling that increases external job prospects.

In contrast, employee recognition did not have a statistically significant relationship with attrition.

IV. CONCLUSION

The findings demonstrate that employee attrition is a multifaceted phenomenon influenced by demographic characteristics, job level, work arrangements, and organizational context. Notably, attrition risk was highest among senior employees, remote workers, highly educated staff, and those with strong career mobility indicators, such as promotions and leadership opportunities. Contrary to conventional assumptions, factors traditionally viewed as positive, such as work and life balance, company reputation, and innovation opportunities were associated with increased attrition, suggesting that employee capability and marketability play a critical role in turnover decisions.

The logistic regression results provide strong evidence that employee attrition is predictable, preventable, and influenced more by workplace experience than compensation alone. By leveraging these data-driven insights, organizations can proactively reduce turnover, retain high-value talent, and build more resilient workforces.

RECOMMENDATIONS

Based on the results, the following data-driven recommendations are proposed:

1. Organizations should prioritize retention strategies for male, senior, highly educated, and high-performing employees, who demonstrate disproportionately high attrition risk.
2. Given the strong association between remote work and attrition, organizations should strengthen engagement, mentoring, and career visibility mechanisms for remote employees.
3. Employees experiencing promotions and leadership opportunities may require structured career pathways, long-term incentives, and succession planning to reduce external mobility.
4. Positive indicators such as good work–life balance and strong organizational reputation should not be assumed to reduce attrition; instead, they should be monitored as potential signals of employee readiness to exit.
5. One-size-fits-all retention approaches may be ineffective. Tailored interventions based on job level, family status, and career stage are likely to yield better outcomes.
6. Investigate why employees reporting high work-life balance leave at higher rates; potentially align flexible policies with long-term career pathways and organizational loyalty.
7. Overall, a data-driven retention strategy focusing on high-risk employee segments, career pathways, and engagement in remote and senior roles is recommended to effectively reduce TURNOVER.

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