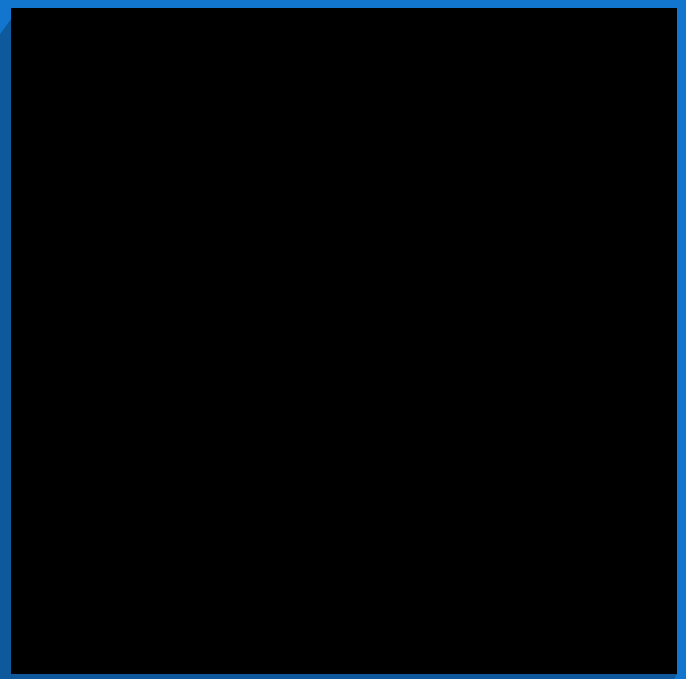

Analyzing Employee Turnover at Acme Aroma

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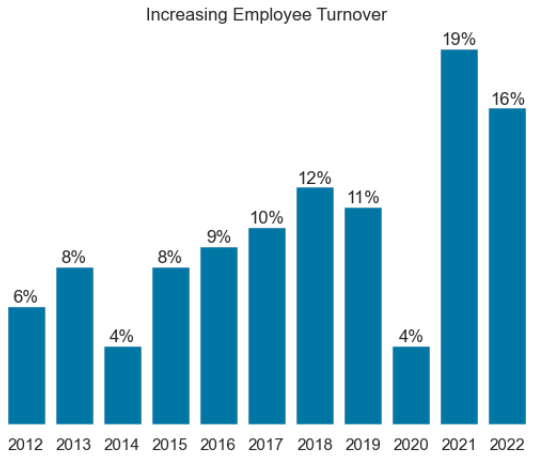
Contents

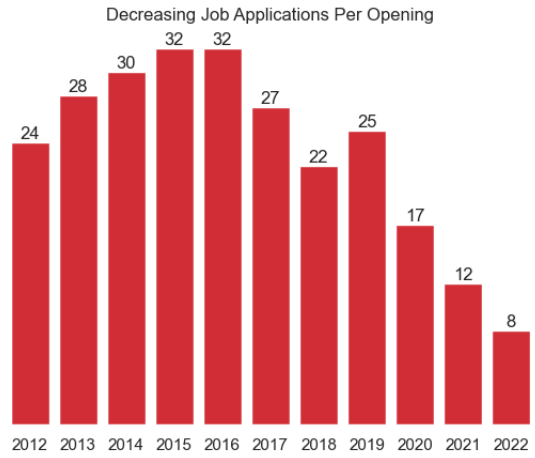
Problem

Increasing Employee Turnover

Increasing employee turnover has placed a strain on Acme operations. *Turnover has increased significantly over the last several years, increasing from a previous high of 12% in 2018 to 19% and 16% in 2021 and 2022*, respectively. Employee surveys show a decrease in satisfaction from 3.4 to 2.7 during this same period.

Interest in employment at Acme Aroma is decreasing**.** The number of job applications per opening has decreased over time, *down from a peak of 32 applicants per role in 2016, down to 8 interested applicants in 2022*.





The acquisition cost of new employees is increasing. Increased turnover has increased hiring and training costs. *From 2021 to 2022, the acquisition cost of a new employee has doubled from ₹15k to ₹30k.*

Additional analysis and predictive insights into employee turnover and retention is needed. *We will use predictive analytics to understand and mitigate turnover*. The objective is to determine which employees are at high-risk for turnover, and what should be done to reduce it.

Approach

Turnover Model for Employee Flight Score

We developed an employee turnover model *to determine which employees are at high risk for turnover* (a flight score).

The model includes key variables associated with high employee turnover and provides statistical support to the initiative recommendation that is most likely to help Acme Aroma mitigate turnover and aid further workforce planning.

Acme Aroma's human resources information system (HRIS) is the data source. *The key variable we aim to predict is Attrition* which we refer to as turnover. The variables for correlation analysis are those that are relevant to the initiative recommendations determined by the conjoint analysis on employee experience.

Key predictive variables as related to each initiative:

Monthly Income: Increase base pay for all employees.

Training Times Last Year: Provide additional professional development.

Environment Satisfaction: Improve workplace flexibility by allowing work-from-home.

Work Life Balance: Improve work-life balance by reducing the amount of required business travel.

Job Satisfaction: Begin employee appreciation initiatives to increase employee job satisfaction.

We utilized a logistic regression model, a classification model that allows us to *describe and predict employee turnover* with these key variables.

This type of model provides us with insight into which of these key variables best explains employee turnover, which in turn *provides guidance on which initiative is likely to be most impactful.*

A well performing model can be used to predict future turnover when given new employee survey data, providing valuable *guidance to future workforce planning.*

We *evaluate the model performance* with the following metrics that gauge prediction ability.

False positives (Type I errors) represent when the model predicts an employee will leave when they do not.

False negatives (Type II errors) represent when the model predicts an employee will not leave when they do leave.

The *F1 Score*, a well-rounded performance metric ranging from 0 to 1, allows us to assess the model's ability to accurately identify and predict positive cases of turnover. A high F1-score (closer to 1) indicates that the model effectively captures true positive cases and minimizes false positives and false negatives.

Insights

Correlation-Based Insights on Employee Turnover

What are the most likely reasons for turnover?

A correlation analysis determined that work-life balance, percent salary hike, and job satisfaction display robust negative correlations with employee turnover, implying their potential to explain turnover trends.

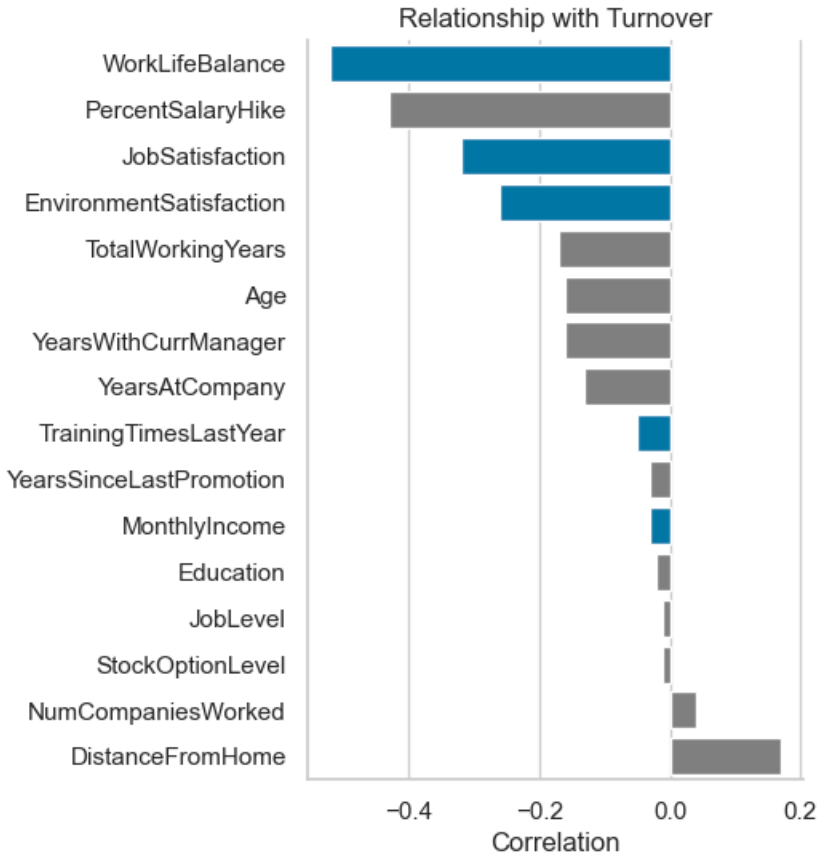
These negative correlations suggest that *reductions in work-life balance, percent salary hike and job satisfaction are associated with increased employee turnover.*

Further exploration of the data revealed that about 8% of employees (346) in the dataset rated work-life balance as less than 2 (”Good”) on a 1-4 scale. Notably this is 50% of the reported turnover at 16%.

The impact of work-life balance is a core finding suggesting that reducing the amount of business travel required may have a significant impact on employee turnover.

Additionally, employees receiving a marginal percent salary increase may perceive their compensation as inadequate, increase the chance of turnover. This is not a current initiative option.

Notably, not all initiative options (blue on right) strongly correlate with turnover. This highlights the intricate nature of identifying and mitigating the potential for turnover.



Insights

Model Description and Performance

Model Description:

The model includes the *key variables associated with each initiative*: monthly income, how often training is provided, how satisfied employees are with their work environment and job, and work-life balance.

Additionally, the model includes *other variables with notable correlation with turnover such as*: the percentage their salary has increased, how long they've worked in total and at the current company, their age, the time they've spent with their current manager, and the time since their last promotion.

The goal is to use these variables understand the complex dynamics of employee turnover and provide actionable insights for employee retention strategies.

F1 Score:

The model achieved an F1 score of 0.94 for the negative class (non-turnover) and 0.71 for the positive class (employee turnover). This indicates that *the model is highly effective at identifying non-turnover cases, and moderately effective at identifying actual turnover cases.*

False Positive Rate:

The false positive rate, which represents cases wrongly predicted as turnover when they are not, was 9.25%. *This means that about 9.25% of the predictions for turnover were incorrect, indicating a relatively low rate of false alarms.*

False Negative Rate:

The false negative rate, which represents cases wrongly predicted as non-turnover when they is turnover, was 15.46%. *This indicates that about 15.46% of actual turnover cases were not identified by the model.*

Overall, the model demonstrates strong performance in accurately predicting non-turnover cases, while also providing reasonable predictions for turnover cases. While there is room for improvement in reducing false negatives, the model's ability to keep false positives low suggests it can be a valuable tool for making informed decisions about employee retention strategies.

Prediction	F1-Score
Non-Turnover	0.94
Turnover	0.71

False Positives	False Negatives
9.25%	15.46%

Insights

Analyzing Turnover Associated Factors

The relationship between various factors and employee turnover as determined by the model is expressed here in percent change in odds. The relationships here mirror the correlation-based analysis. Two key predictors stand out: Work-Life Balance and Percent Salary Hike

Work-Life Balance:

Work-Life Balance has a significant impact on turnover*. A standard deviation increase in Work-Life Balance is associated with a decrease in the odds of turnover by approximately* 86.5% to 90.3%

This suggests that when employees perceive a better work-life balance, they are significantly less likely to leave the company.

Percent Salary Hike:

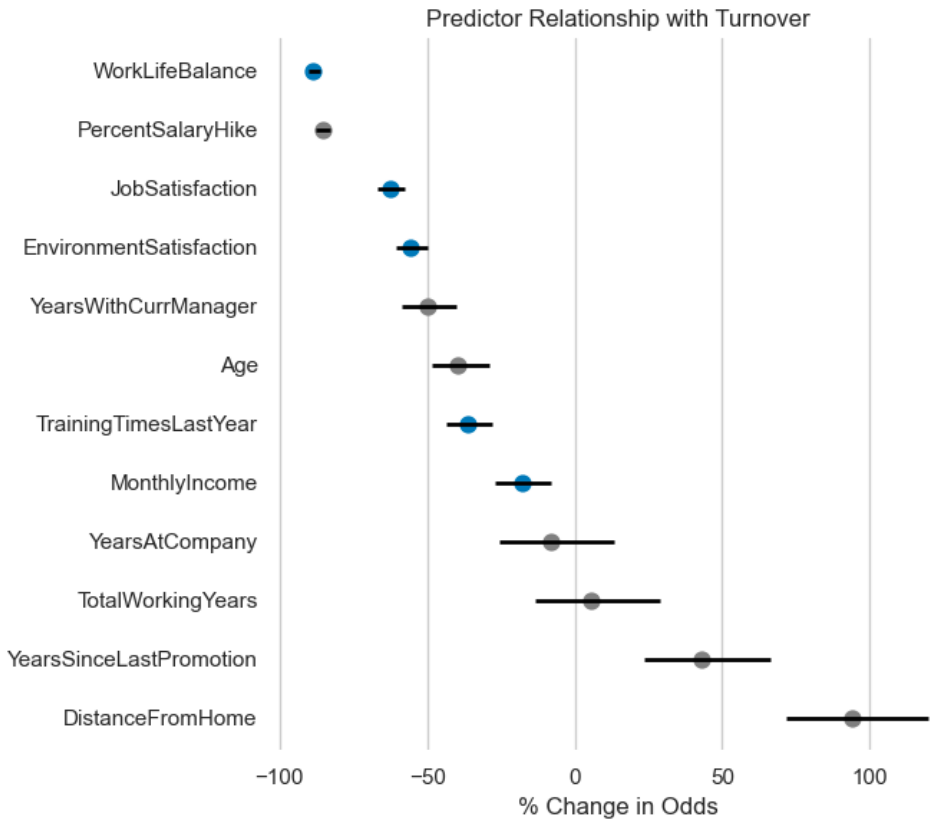
Percent Salary Hike also plays a crucial role in turnover. *A one standard deviation increase in Percent Salary Hike is linked to a decrease in the odds of turnover by approximately 82.8% to 87.8%*

This suggest that employees who receive higher salary hikes are less likely to leave.

It may be beneficial to consider compensation strategies, as this is not a current initiative option.

Other Factors:

Other initiative factors are not as strongly related. Job satisfaction, environment satisfaction, amount of training and monthly income all fall below a 65% change in odds with more uncertainty in estimation.



Recommendation

Limit Required Business Travel

Limiting required business travel to improve work life balance is a reasonable initiative given the strong negative correlation of work life balance with employee turnover.

This option is projected to result in a **3% reduction in turnover and savings of approximately ₹126,225,521,** based on the model and sample data.

The model has strong ability to effectively capture employee turnover trends. Implementing the model is suggested. Rationale follows.

Model Performance Strengthens Confidence:

The high F1 score of 0.94 for non-turnover cases highlights the model's accuracy in identifying employees likely to remain with the company. This robust prediction capacity boosts confidence in the projected 3% percent reduction estimate.

In addition, while the F1 score of 0.71 for turnover cases is not ideal, the model is still to capture these instances relatively well. This base model can be improved with further optimization.

Balancing False Positives and False Negatives:

The relatively low false positive rate of 9.25% indicates that the model minimizes unnecessary interventions or resource allocation for employees who are unlikely to leave.

The challenge is the false negative rate of 15.46%, which indicates a potential risk of losing valuable employees who may have been retained with more accurate predictions.

Strategic Alignment and Financial Gain:

The initiative's expected impact on reducing turnover is underscored by the estimated savings of approximately ₹126,225,521 through employee retention.

This correlates with the projected influence of reduced business travel on employee work-life balance and possibly job satisfaction and engagement.

Limitations

Uncertainty in Analysis

The logistic regression model allows us to relate employee attrition with key variables related to our workforce planning initiatives. This model has *limited explanatory power* and the key variables utilized in the model likely not the only factors that influence attrition. Including additional predictor variables could strengthen the performance of the model.

We aim to reduce the impact of *bias from confounding variables* by including variables that possibly influence our key variables but are outside the scope of our initiatives. If these influences are particularly strong, this can lead to difficulty in interpreting the effect of single variables.

In addition, any strong correlations between the variables and employee attrition could also be influenced by *additional factors outside the scope of our available data.*

There could also be bias from the data collection method, employee surveys. We have no demographic data *on which and how many employees in the organization completed the surveys compared to those that did not.*

In addition, we assume that employees that did complete the survey provided accurate information regarding their experiences.

For example, employees that are more likely to leave the organization could refuse to answer all survey questions or even complete the survey at all. Data collected from only the most or moderately engaged employees and not the completely disengaged could lead to bias in our analysis and impact final recommendations.

The data is unbalanced and skewed towards employees that remain at Acme, meaning there is less information and more difficulty in determining the attributes of employees that leave the organization.

We address this issue by *generating plausible synthetic data that resemble the data of employees that leave.*

Opportunities for additional data collection and analysis should be considered, especially considering that the organization and employee sentiment could change over time. *Including the opportunity for full written responses in future surveys* could provide rich data regarding employee sentiment, in turn providing insight into additional factors not previously considered for analysis.