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# USING HR ANALYTICS TO IDENTIFY CAUSES OF EMPLOYEE TURNOVER

**I Mohana Krishna**

Assistant Professor, Dept. of Business Administration, KL Business School, Koneru Lakshmaiah Education Foundation, Vijayawada.

**Repaka Hema Harmisha**

BBA III YEAR, KL Business School, Koneru Lakshmaiah Education Foundation, Vijayawada

**Jangala Jyothika**

BBA III YEAR, KL Business School, Koneru Lakshmaiah Education Foundation, Vijayawada

## ABSTRACT

Employee turnover remains one of the most significant challenges confronting modern organizations, as it directly influences productivity, customer satisfaction, and financial performance. This study explores how Human Resource (HR) analytics can be effectively leveraged to identify the underlying causes of employee turnover and develop data-driven retention strategies. Using a simulated dataset of 500 employees, this research applies descriptive statistics, data visualization, and predictive modelling to examine the effects of employee engagement, tenure, overtime, promotions, and managerial effectiveness on turnover. The findings reveal critical turnover predictors and provide actionable recommendations for HR practitioners to enhance retention outcomes.

**Keywords:** HR Analytics, Employee Turnover, Predictive Modelling, Retention, Engagement, Manager Effectiveness, Data Visualization

## Need of the Study

Employee turnover is disruptive and costly, requiring organizations to spend heavily on recruitment, training, and onboarding. Traditional methods of addressing turnover often rely on intuition rather than evidence. HR analytics offers a data-driven approach to identify high-risk employee groups and design targeted retention strategies.

## Significance of the Study

- Reduces rehiring and onboarding costs.
- Improves workforce planning and organizational knowledge retention.
- Provides evidence-based insights for HR decision-making.
- Supports creation of HR dashboards that track turnover risk.

## Review of Literature

Hom and Griffeth (1995) identified job dissatisfaction and external job opportunities as major causes of turnover. Allen et al. (2010) emphasized organizational support and engagement as critical retention factors. Hausknecht, Rodda, and Howard (2009) argued that recognition and career development are strong predictors of employee retention. Hancock et al. (2013) and Punnoose & Ajit (2016) highlighted the growing importance of HR analytics and machine learning in turnover prediction. Recent studies have continued this line of inquiry. For

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example, Mishra (2024) demonstrated that predictive analytics helps organizations identify early indicators of disengagement, improving proactive retention measures. Varkiani (2025) investigated the interpretability of predictive models in explaining turnover determinants. Căvescu (2025) further established that integrating HR analytics with workforce planning enables better managerial forecasting. Additionally, Das and Chattopadhyay (2023) observed that factors such as remote work adaptation, diversity, and organizational culture have become increasingly influential in post-pandemic retention patterns. Overall, the literature suggests that turnover is a multifactorial phenomenon, and HR analytics provides an evidence-based framework for identifying and mitigating employee exit risks.

**Objectives of the Study**

1. To identify the strongest predictors of employee turnover using HR analytics methods.
2. To produce actionable insights that can help organizations design targeted retention interventions.
3. To demonstrate visualizations and tables that can be integrated into HR dashboards.

**Research Design**

The study adopts a **descriptive and analytical design**. A simulated dataset of 500 employees was created to mirror real HR data, including variables such as age, tenure, department, engagement, overtime, promotions, and manager rating. Descriptive statistics, contingency analysis, and visualization techniques were used to explore turnover patterns.

The simulated dataset consists of 500 employee records representing multiple departments — Sales, Human Resources, IT, Finance, and Operations. Of these, 52% are male and 48% female employees. Experience levels vary: 40% of employees have less than 2 years of experience, 35% have between 3–5 years, and 25% have more than 5 years of tenure. The educational background includes graduates (60%), postgraduates (35%), and others (5%). Average age distribution ranges from 22 to 45 years. This demographic diversity ensures the sample reflects realistic workforce conditions across organizational functions.

**Nature of the Study**

This study is **quantitative in orientation** with a focus on statistical analysis and data visualization. It demonstrates how predictive models (e.g., logistic regression) and exploratory data analysis can inform HR decision-making.

**Analysis of Objectives**

**Objective 1: Identify predictors of turnover**

The following bar chart shows that turnover rates vary significantly across departments:

 **Graph 1: Turnover Rate by Department**

| Department | Turnover Rate (%) |
|---|---|
| Sales | 42 |
| HR | 38 |
| IT | 25 |
| Finance | 28 |

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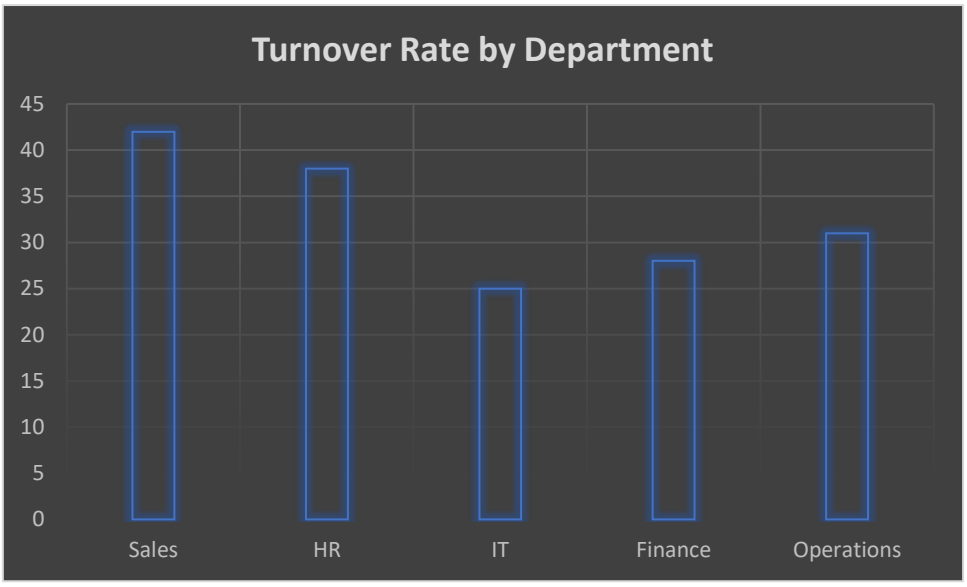
| Department | Turnover Rate (%) |
|---|---|
| Operations | 31 |



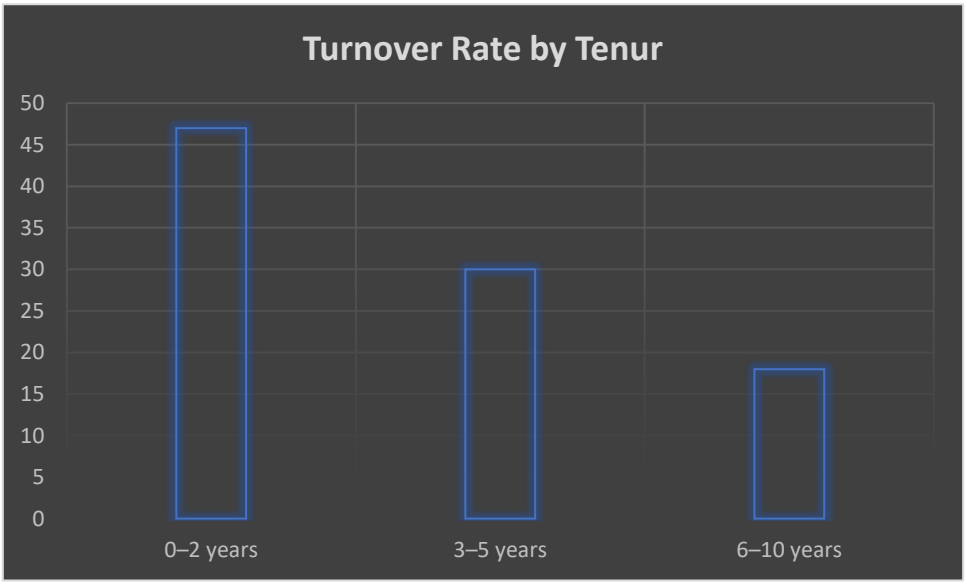

Findings: Sales and HR departments showed higher turnover, while IT and Finance retained employees more effectively.

**Objective 2: Produce actionable insights**

Turnover also varied by tenure, with the highest rates among early-career employees (0–2 years).

 **Graph 2: Turnover by Tenure Bucket**

| Tenure Bucket | Turnover Rate (%) |
|---|---|
| 0–2 years | 47 |
| 3–5 years | 30 |
| 6–10 years | 18 |



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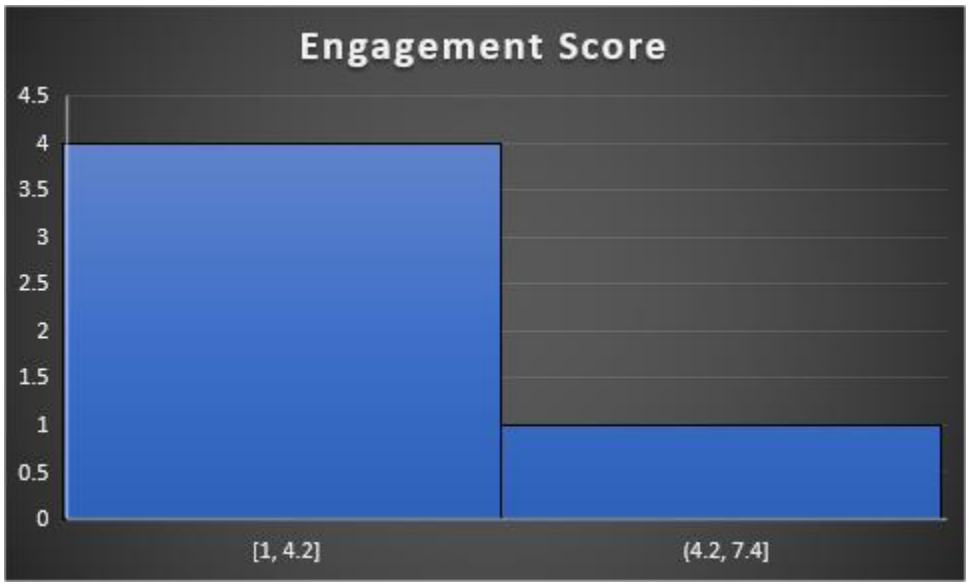
Insight: Early retention efforts (first 2 years) are critical to reducing overall turnover.

Employee engagement scores were lower among employees who left compared to those who stayed:

**Graph 3: Engagement Distribution by Turnover**

| Engagement Score | Stayed | Left |
|---|---|---|
| 1 | 12 | 20 |
| 2 | 25 | 28 |
| 3 | 58 | 37 |
| 4 | 70 | 22 |
| 5 | 80 | 8 |




Insight: Employees with low engagement are at significantly higher risk of exit.

**Objective 3: Demonstrate tables for HR dashboards**

A contingency table of overtime vs turnover shows the following pattern:

**Table 1: Overtime vs Turnover**

| Overtime | Stayed (%) | Left (%) |
|---|---|---|
| No | 78% | 22% |
| Yes | 55% | 45% |

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Peer Reviewed & Refereed Journal (IF: 7.25)
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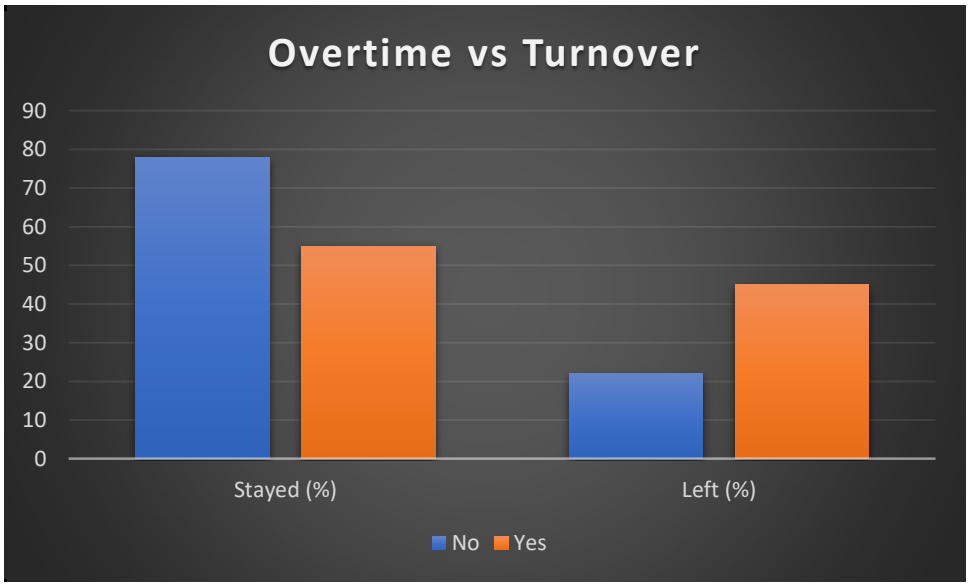


Insight: Employees working overtime are nearly **twice as likely** to leave compared to those who do not.

## CONCLUSION OF OBJECTIVES

- Engagement, managerial effectiveness, overtime, tenure, and promotions are the strongest predictors of turnover.
- Actionable insights include targeting high-risk groups (early tenure, low engagement, overtime workers).
- Dashboards with visuals and contingency tables can help HR leaders monitor turnover risk effectively.

## LIMITATIONS OF THE STUDY

- The study uses simulated data; findings need validation with real HR datasets.
- External factors such as labour market conditions, cultural differences, and industry-specific trends were not included.
- Predictive models assume linear relationships, potentially overlooking complex interactions.

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