# High Recall Oriented Employee Attrition Prediction using Stacking Ensemble Model

**Under DSKC, Miranda House, University of Delhi**

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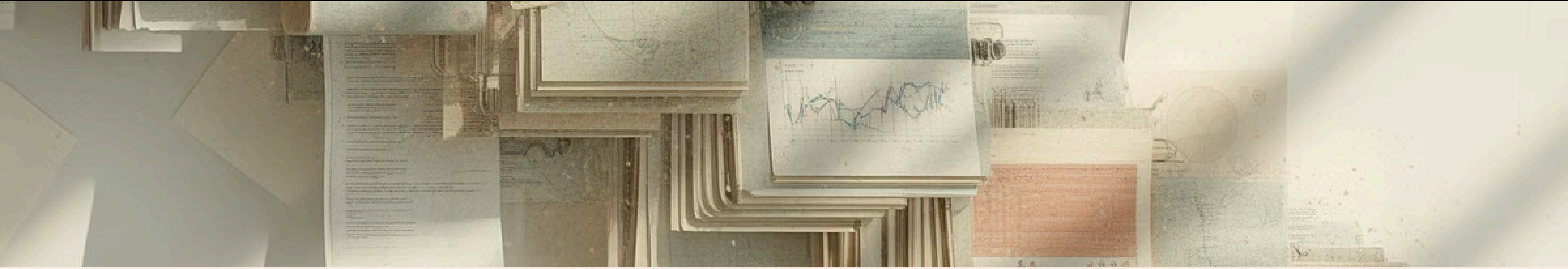


# Abstract


### 1 High-Recall Prediction Focus

Predicting employee attrition with a **high-recall ML model** designed to identify potential departures before they occur

### 2 Stacking Ensemble Method

Leveraging Random Forest, XGBoost & LightGBM with ExtraTrees as the meta learner to achieve superior prediction performance

### 3 Sophisticated Preprocessing

Employing label encoding, feature selection, SMOTE balancing, and scaling to optimize the IBM HR dataset and additional public HR datasets

### 4 Performance-Focused Tuning

Achieving **0.81 Recall** and **0.83 F1 score** through manual hyperparameter tuning and custom threshold optimization with consistent cross-dataset validation

# Motivation

1. Employee attrition leads to loss of productivity, hiring costs, and disruption in team dynamics which effects company reputation also.

2. Not all employees are equal; companies care most about retaining high-value talent.

3. Traditional models focus on accuracy but may miss the critical "leaving" cases.

4. Our goal: Maximize recall to detect as many attrition cases as possible, even at the cost of some false positives.

5. This approach allows organizations to proactively engage with at-risk employees before they leave.

# Model Exploration & Final Choice

1 **Started with Logistic Regression, SVM, and shallow Neural Networks**

Observed low F1 & recall, especially on minority class and over-fitting

2 **Tree-based models like RF, XGBoost, and LGBM showed stronger performance**

Inspired by stacking strategies proposed in recent research [7] we explored **Stacking Ensemble**

3 **Final model = RF + XGB + LGBM → Extra Trees**

**Recall boost** confirmed

| MODEL NAME | Recall(minority class) | F1(minority class) |
|---|---|---|
| logistic regression | 0.72 | 0.55 |
| SVM | 0.53 | 0.39 |
| FNN | 0.55 | 0.54 |
| MLP | 0.55 | 0.6 |
| CNN | 0.53 | 0.54 |
| LGBM | 0.53 | 0.51 |
| random forest | 0.49 | 0.51 |
| XGBoost | 0.6 | 0.52 |
| easy ensemble | 0.44 | 0.56 |
| Stacking Ensemble | 0.83 | 0.57 |

# Objectives

1

Build a predictive model that generalizes across datasets.

2

Focus on **recall for minority class** ("Yes" = Attrition).

3

Use **stacking ensemble classifier** to combine strengths of multiple classifiers.

4

Tune hyperparameters manually based on performance.

# Dataset(s) Used:

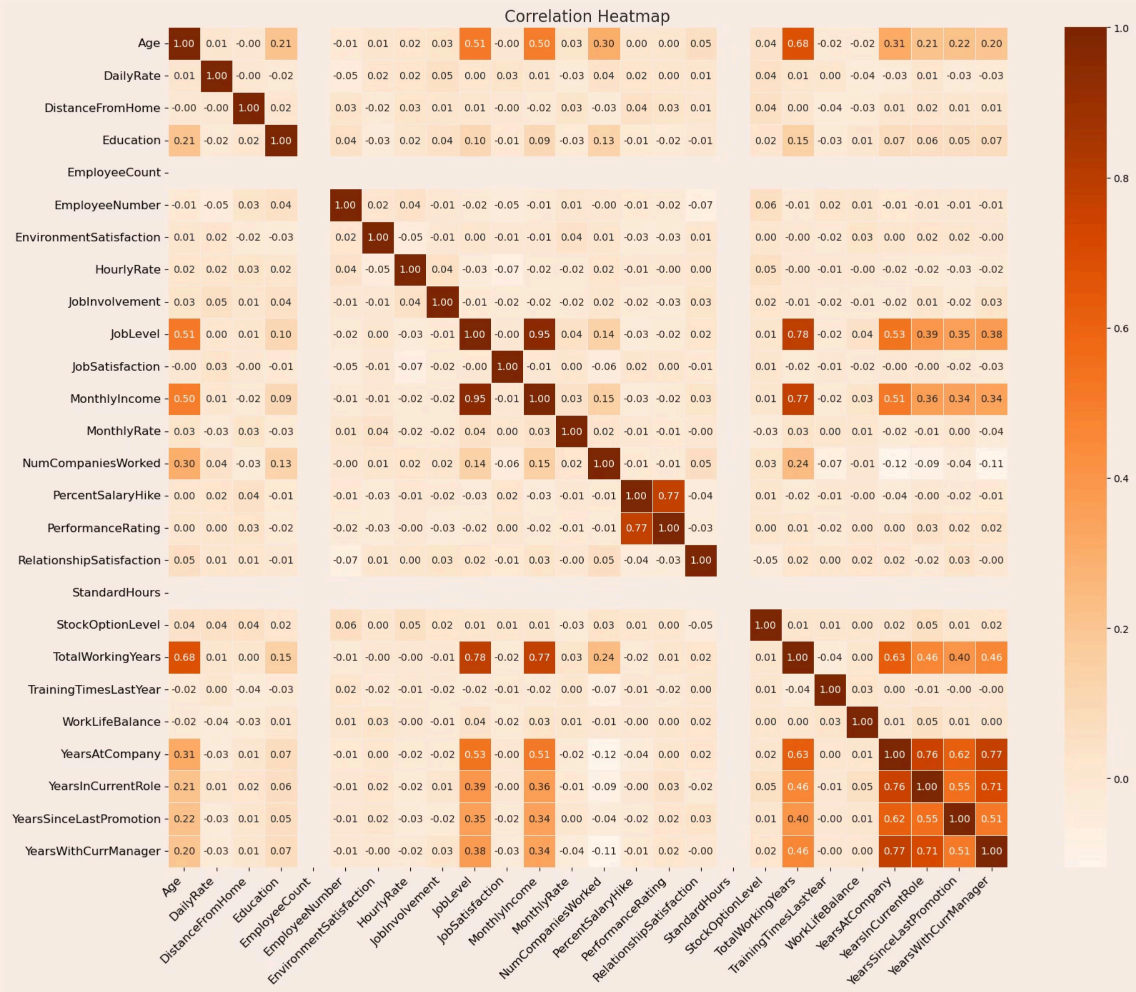
*We evaluated our model on the IBM dataset as well as additional HR datasets to test its generalization across diverse employee profiles.*

| DATASET | features | Records | Class imbalance |
|---|---|---|---|
| **SYNTHETIC EMPLOYEE ATTRITION DATASET BY IBM** | 35 | 1470 | 16:84 |
| **WATSON HEALTHCARE DATASET** | 35 | 1676 | 13:87 |
| **SYNTHETIC EMPLOYEE ATTRITION DATASET BY STEALTH TECHNOLOGIES** | 23 | 14900 test<br>59600 train | 47:52 |

- IBM dataset used for training + tuning
- Other datasets used to evaluate cross-domain generalizability
- All datasets shared common target: Attrition (Yes/No)

# Feature overview for IBM dataset

| Category | Features |
|---|---|
| Demographics | Age, Gender, MaritalStatus |
| Job Role & Department | JobRole, Department, JobLevel, JobInvolvement, YearsAtCompany, YearsInCurrentRole, YearsSinceLastPromotion, YearsWithCurrManager |
| Compensation | MonthlyIncome, MonthlyRate, DailyRate, HourlyRate, StockOptionLevel, PercentSalaryHike |
| Performance & Satisfaction | JobSatisfaction, EnvironmentSatisfaction, PerformanceRating, RelationshipSatisfaction, WorkLifeBalance |
| Education & Training | Education, EducationField, TrainingTimesLastYear |
| Experience & Background | TotalWorkingYears, NumCompaniesWorked, DistanceFromHome, OverTime, BusinessTravel |




**Features Dropped:**

**EmployeeCount, Over18, StandardHours:** ***because of redundancy***

**MonthlyIncome:** ***from the correlation heatmap we can see that MonthlyIncome and JobLevel are highly corrleted***

# Preprocessing and handling Imbalance

### 1 RAW DATA

Starting point with original dataset features

### 2 Cleaning

Removed some features as explained in the previous slide

### 3 Encoding

Used Label encoding to convert Categorical features into numerical

(eg: Gender, JobRole)

### 4 SMOTE

Since the dataset was quiet imbalanced, we applied SMOTE to balance the classes in the train data

### 5 Scaling

Used Standard Scaler to normalize numerical features

### 6 Model Input

Final processed data ready for model training

# Model architecture

***We meticulously tested all parameters of each model manually to achieve optimal results***

**Input Dataset**

Preprocessed HR data with balanced classes

**Base Learners**

**Random Forest**

[n_estimators=120,max_depth=5,min_samples_split=10,min_samples_leaf=5,max_features='sqrt',bootstrap=True,classweight='balanced_subsample']

**XGBoost**

[use_label_encoder=False,eval_metric='logloss',n_estimators=100,learning_rate=0.03,max_depth=3,subsample=0.6,colsample_bytree=0.6,scale_pos_weight=2,reg_lambda=10,reg_alpha=2,gamma=10]

**LightGBM**

[n_estimators=100,learning_rate=0.05,max_depth=5,subsample=0.7,colsample_bytree=0.7,class_weight='balanced',reg_lambda=5,reg_alpha=1]

**Meta Learner**

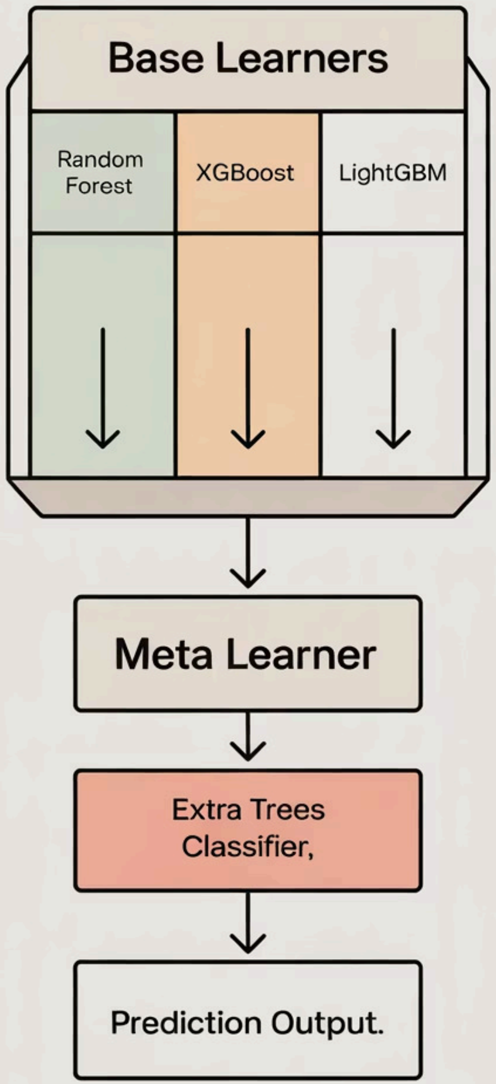
**ExtraTrees Classifier**

[n_estimators=100,max_depth=6,min_samples_split=10,min_samples_leaf=5,max_features='sqrt',class_weight='balanced',n_jobs=-1]

Combines predictions from base models

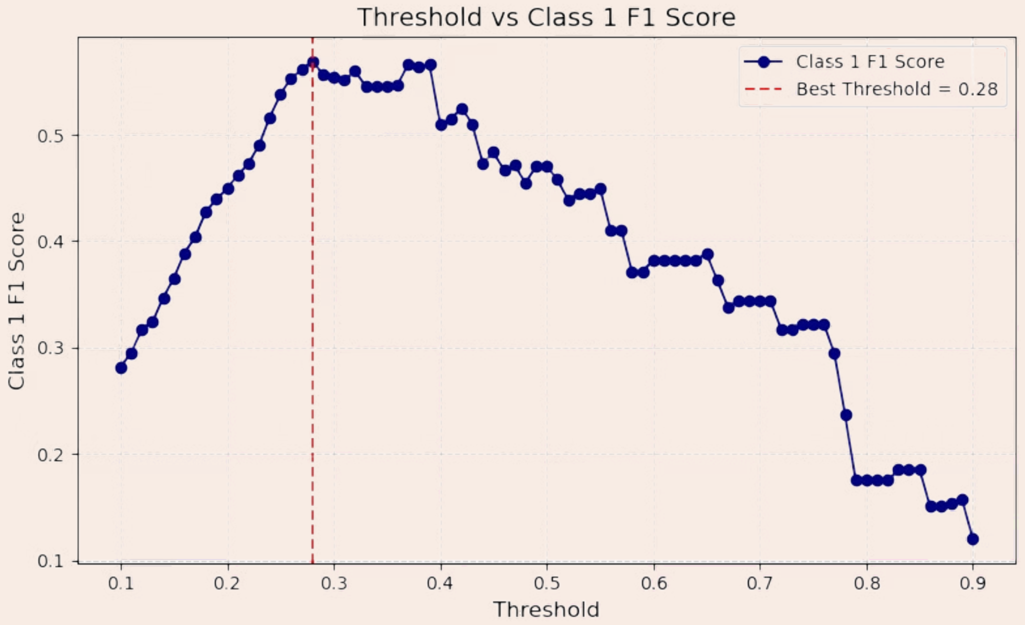
**Final Prediction**

Optimized for high recall on attrition class



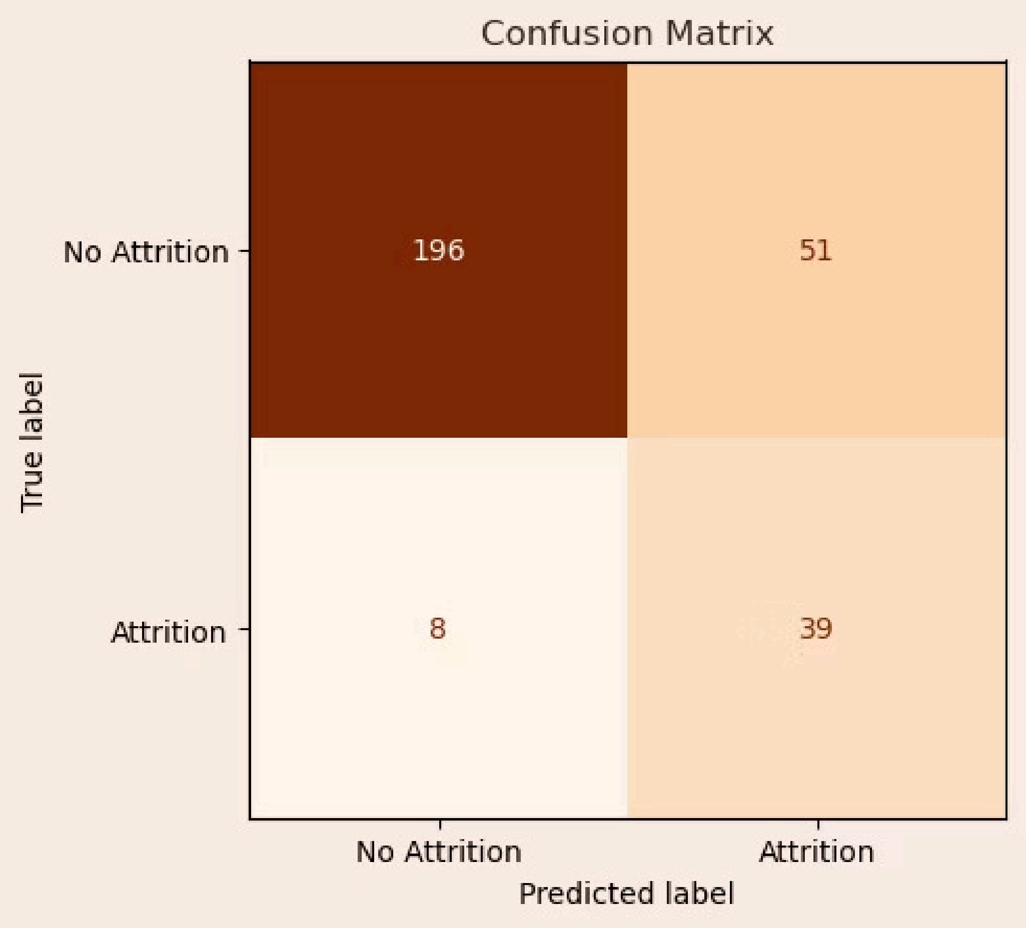
# Threshold Tuning & F1 Optimization

1. After training, we performed threshold tuning to optimize performance
2. Used model's predicted probabilities
3. Iterated threshold from **0.1 to 0.9 (step = 0.01)**
4. Evaluated each on **class 1 F1-score**
5. Final selected threshold = 0.28
6. Helped improve **recall** and **F1-score** without retraining the model




*Tuning the threshold allowed us to better balance false positives and false negatives, especially important for the minority class*

# Results Summary (on IBM Dataset)




| Metric | Score |
| --- | --- |
| Accuracy | 0.80 |
| Precision | 0.88 |
| **Recall** | **0.81** |
| F1 score | 0.83 |
| Support | 294 |
| **Recall (minority class)** | **0.83** |

***High Recall of positive attrition cases (0.83)*** ***ensures most attrition cases are detected,*** ***aligning with our real-world objective of*** **early identification & intervention.**

# Comparison with State-of-the-Art Model

Reference Study: *"Developing a hybrid machine learning model for employee turnover prediction: Integrating LightGBM and genetic algorithms"* Hojat Talebi et al., *Journal of Open Innovation: Technology, Market, and Complexity*, Volume 11 (2025), Article ID: 100557 DOI: **https://doi.org/10.1016/j.joitmc.2025.100557**

## *It Uses GA for feature selection + LightGBM for classification*

### Performance Comparison

**Proposed model outperforms SOTA** across **all key metrics**

### Ensemble Advantage

Stacking ensemble captures diverse learning patterns from RF, XGBoost & LGBM

### Threshold Tuning

Additional threshold tuning improves recall (crucial for attrition prediction)

| Metric | SOTA Model | Proposed Model |
|---|---|---|
| F1-Score | 0.73 | **0.83** |
| Precision | 0.75 | **0.88** |
| Recall | 0.72 | **0.81** |
| Accuracy | 0.78 | **0.80** |

# Cross-Dataset Validation

***The model was tested on two additional datasets with different class balances and feature dimensions, to assess its generalization and recall consistency.***

| Dataset | Records | Features | Class Balance | Accuracy | Weighted Recall | Weighted F1-score |
|---|---|---|---|---|---|---|
| IBM | 294 | 35 | 16:84 | 0.80 | **0.81** | **0.83** |
| Watson | 336 | 35 | 13:87 | 0.93 | **0.93** | **0.93** |
| StealthTech | 14,900 | 23 | 47:52 | 0.74 | **0.74** | **0.74** |

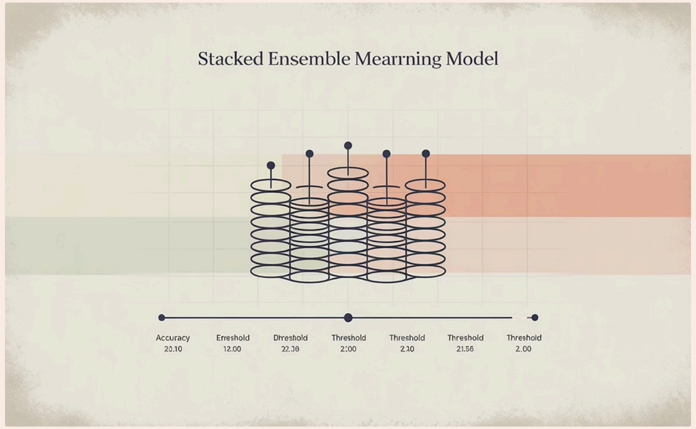
- High weighted metrics across all datasets show strong generalization
- Watson Healthcare dataset had **best overall metrics**, even with class imbalance
- Model adapts well to both **imbalanced** and **balanced** scenarios
- Reflects strong potential for real-world implementation across domains

# Business Impact

- **High Recall = Early Identification of At-Risk Employees** → Even if few false positives exist, better to **consult and retain proactively**
- **Helps in flagging "Asset-Class" Employees** → Companies can't afford to lose top performers
- **Supports Strategic HR Decisions** → Personalized retention plans, counseling, incentive tweaking
- **Saves Cost of Rehiring & Retraining** → Retaining employees is cheaper than replacing them

***"Missing an attrition case can be costlier than wrongly flagging one'*** **– so high recall gives the company that protective edge.**

# Conclusion

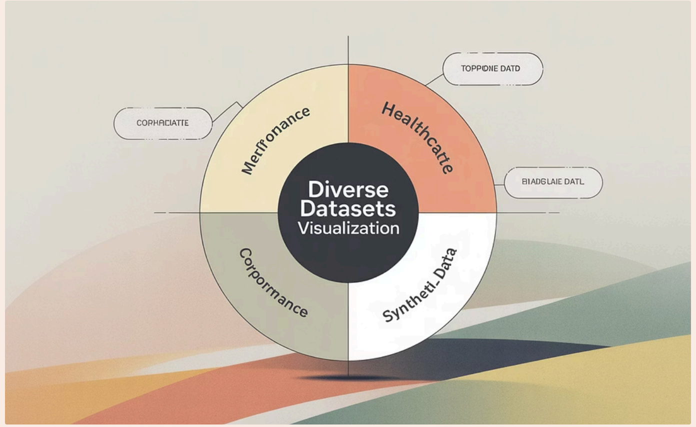



## High-Performance Predictor

**Stacked ensemble model + threshold tuning** creates a powerful attrition prediction system


## Recall-Focused Strategy

**Recall-focused approach** aligns with modern HR priorities by catching all potential exits




## Cross-Dataset Performance

**Generalizes well** across diverse datasets including corporate, healthcare, and synthetic environments

**"Our model doesn't just predict attrition — it empowers HR to prevent it."**

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# Thank you