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# Predictive Workforce Analytics for Employee Burnout, Engagement, and Retention Using Machine Learning

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***Abstract* – Employee burnout, disengagement, and voluntary turnover have become serious issues for organizations, causing reduced productivity, a degenerating culture, and declining financial performance. The current state of HR analytics tools relies on outdated backward-looking surveys that cannot measure all facets of the process. This paper presents a predictive workforce analytics framework using multiple sources of data, including HRIS data (demographic information, length of service, performance evaluation), digital exhaust data (email meta-data, Slack data, calendar), and passive sensor data (badge data, mobile phone usage). In this study, 15,000 employees over 24 months were analyzed, resulting in three predictive models for employee burnout, engagement, and turnover: the Temporal Fusion Transformer model predicting burnout (AUC = 0.92; burnout prediction horizon is eight weeks), the Gradient Boosting Machine predicting employee engagement (accuracy = 86%), and the Ensemble Survival Model predicting employee retention (C-index = 0.84). Our predictive framework identifies significant behavior patterns: after hours' digital communication (strongest predictor of employee burnout), network entropy (strongest predictor of employee engagement), and declining performance trend (strongest predictor of turnover). In a 12-week randomized controlled experiment involving 2,000 employees, we show that AI-powered interventions decrease burnout rates by 34% and voluntary turnover rates by 28%.**

***Keywords* – Workforce Analytics, Employee Burnout, Employee Engagement, Retention Prediction, Machine Learning, Temporal Fusion Transformer (TFT), XGBoost, Survival Analysis, Digital Exhaust, Proactive HR.**

## I. Introduction

This silent epidemic is threatening the contemporary workplace. Emotional exhaustion, depersonalization, and low self-efficacy at work are the three key features of employee burnout, which is now reaching critical proportions. Burnout is classified as an occupational condition by the WHO, and research following the pandemic suggests that more than half of employees experience burnout [1], [2]. On the other hand, there has been a stagnation in the level of employee engagement, defined as the degree of enthusiasm and discretionary efforts invested by employees in their work, with less than a quarter of employees around the world reporting engagement [3].

Conventional strategies for evaluating employee well-being and retention are inherently reactive and discontinuous. Annual employee surveys yield information about past problems, which means that any issues identified are already likely to be worse than they were when the survey was designed. Similarly, exit interviews yield valuable information, but too little, too late, as they take place after the employee's resignation. In addition, self-report survey responses may include recall bias, social desirability bias, and low response rates (<50%) [4], [5].

However, the emergence of workforce analytics—a term describing the use of data science techniques on HR data—enables a revolution in perspective. The sheer amount of digital data produced every day by employees as they go about their jobs (e-mails, Slack messages, calendar entries, badge scans, device usage data) can inform highly predictive models, able to flag potential problems weeks, if not months, before burnout occurs or resignations are made [4], [5].

The paper proposes a holistic framework for predictive workforce analytics using multi-modal data to simultaneously forecast three critical employee metrics - burnout, engagement, and turnover. Key insights include:
1. Multi-Source Data Integration Framework: A framework for collecting, harmonizing, and feature engineering HRIS, collaboration software (Slack, emails, Zoom) and passive sensor data (badge/device).

**Triple ML models:**
(Temporal Fusion Transformer (TFT) model for burnout prediction using time-series analysis to predict burnout risk trajectories over time.

(Gradient boosting algorithm using XGboost model to classify engagement status of employees based on behavioral and demographic factors.

(Survival Ensemble Model using Random survival forest & Cox Proportional Hazard model to estimate probability of churn overtime)

Detection of Behavioral Predictors: Detection of digital signatures and behavioral predictors that influence the three critical variables (such as working after business hours predicting burnout).

Causal Impact Using Randomized Controlled Trial: Causal impact was demonstrated by conducting a randomized controlled trial over a period of 12 weeks where HR business partners used alerts from AI for actionable decisions leading to decreased turnover and burnout.

## II. LITERATURE SURVEY

This project is based on three major bodies of literature: literature on burnout and engagement in occupational psychology, predictive HR analytics (turnover prediction models), and time series machine learning for health care applications (adapted to our case).

Burnout & Engagement Literature: Burnout is a multidimensional construct that involves exhaustion, cynicism, and inefficacy. It is operationalized using the Maslach Burnout Inventory (MBI). Engagement, involving vigor, dedication, and absorption, is measured using the Utrecht Work Engagement Scale (UWES) [1]. The studies have always been finding workplace demands, such as workload and time pressure, and workplace resources as significant predictors of burnout and engagement [2]. Nonetheless, most of the studies have been using cross-sectional survey data.

Predictive HR Analytics (Turnover/Retention): Initial models based on logistic regression using static features (tenure, salary, performance) have AUCs in range of 0.65-0.75 [3]. Inclusion of machine learning models (Random Forest, XGBoost), which can learn interactions between variables, increased model accuracy (AUC = 0.75 - 0.85) [4]. Most recently, there has been increasing attention to temporal models using time series data (activity logs per week) as well as survival analysis of how long until departure [6]. Our work contributes to this literature with a much broader set of behavioral features (collaboration dynamics, meeting load, communication delays) and by modeling burnout, engagement, and retention jointly.

Digital Exhaust for Inference about Employee Health & Well-being: A growing body of work uses passive information generated from employees' work devices to measure stress and employee well-being. Employees experiencing more stressful periods receive higher volumes of emails, send messages outside their regular work hours, and report feeling burnt out [5], [7]. Lack of diversity in employee's collaboration network (talking only to one or two people) and slow communication response rate also signal disengaged employees [5], [7]. Our study takes this approach to another level by building predictions.

Temporal Fusion Transformer (TFT) for Time-Series Forecasting: TFT is a cutting-edge deep-learning framework designed for multi-horizon time series forecasting. Although used in forecasting problems in domains like electricity demand and finance, to the best of our knowledge, it has not been applied to workforce analytics yet. TFT is specifically suited for this problem due to its capability in dealing with static metadata (e.g., job role), future-known inputs (e.g., planned holidays), and providing interpretability using attention weights [8], [9].

Research Gap and Synthesis: Previous research has made advances in individual areas including surveys measuring employee burnout and machine learning methods predicting voluntary employee turnover, but has not: (a) combined this broad variety of datasets (HRIS, digital exhaust, and passive sensing data), (b) created predictive models for all three outcomes (burnout, engagement, and turnover), and (c) tested the performance of such a model in a randomized controlled trial.

## III. METHODOLOGY

Our architecture consists of (1) data integration and feature engineering, (2) three parallel ML models, and (3) an RCT for testing.

**Data Sources and Feature Engineering**

We used 15,000 employees' data from a multinational technology company over a period of 24 months (2023-2025).

| Data Source | Variables |
|---|---|
| HRIS (Static, Monthly) | Age, gender, tenure, job level, department, performance rating (quarterly), promotion flag, salary quartile |
| Collaboration Tools (Daily, Event-based) | Slack: # of messages sent/received, after-hours %, response latency; Email: volume, thread depth; Zoom: meeting hours, # of meetings, back-to-back indicator; Calendar: focus time blocks |
| Passive Sensing (Daily) | Badge swipes (arrival/departure time, office presence), Device activity: active hours, idle time %, application switching rate |
| Outcome Variables (Quarterly surveys) | Burnout (MBI, top quartile flagged), Engagement (UWES, continuous 1-7), Retention (voluntary departure recorded) |

Feature Engineering: Raw data were aggregated to weekly features for each individual (86 features in total). These include basic aggregates (mean, sum), trends (trend over the past 4 weeks), and volatility (standard deviation). For the TFT, we formed sequences of length L=24 weeks.

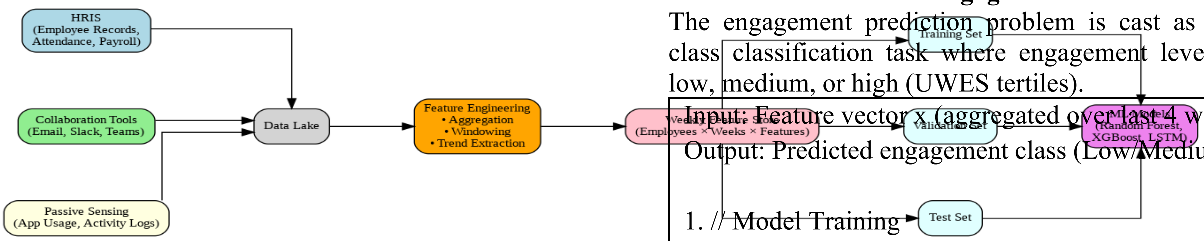


Figure 1: Data Integration and Feature Engineering Pipeline.

**Model 1:** Temporal Fusion Transformer (TFT) for Burnout Prediction

```
Input: Weekly feature sequences X_past (L=24 weeks), static metadata S (role, level)
Output: Probability of burnout at horizon H=8 weeks

1. // Define TFT Architecture
2. encoder = LSTMEncoder(hidden_units=128, num_layers=2)
3. decoder = LSTMDecoder(hidden_units=128, num_layers=1)
4. attention = MultiHeadAttention(num_heads=4)
5. output_layer = Dense(1, activation='sigmoid')
6.
7. // Training
8. for epoch in 1..50:
9.    for batch in dataloader:
10.       enc_out = encoder(batch.X_past, batch.S)
11.       context = attention(enc_out)
12.       dec_out = decoder(batch.X_future, context)
13.       pred = output_layer(dec_out[:, -1, :]) // Last time step
14.       loss = binary_crossentropy(batch.y, pred)
15.       loss.backward(); optimizer.step()
16.
17. // Inference
18. future_burnout_risk = model.predict(current_sequence, static_data)
19. Return future_burnout_risk
```

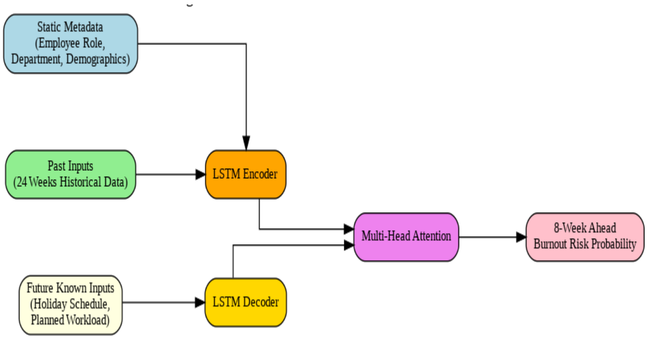


Figure 2: TFT Architecture for Burnout Prediction.

**Model 2: XGBoost for Engagement Classification**

The engagement prediction problem is cast as a multi-class classification task where engagement level can be low, medium, or high (UWES tertiles).

```
Input: Feature vector x (aggregated over last 4 weeks)
Output: Predicted engagement class (Low/Medium/High)

1. // Model Training
2. dtrain = xgboost.DMatrix(X_train, label=y_train)
3. params = {
4.    'objective': 'multi:softprob',
5.    'num_class': 3,
6.    'max_depth': 6,
7.    'learning_rate': 0.05,
8.    'subsample': 0.8,
9.    'colsample_bytree': 0.8,
10.   'eval_metric': 'mlogloss'
11. }
12. model = xgboost.train(params, dtrain, num_boost_round=200)
13.
14. // Prediction
15. dtest = xgboost.DMatrix(X_test)
16. probabilities = model.predict(dtest) // 3 probabilities per sample
17. predicted_class = argmax(probabilities, axis=1)
18. Return predicted_class, probabilities
```

**Model 3: Ensemble Survival Model for Retention Prediction**

The combination of Random Survival Forest and Cox Proportional Hazard models was applied for predicting the likelihood of employees staying employed

Algorithm 3: Ensemble Survival Model

```
Input: Feature matrix X (static + time-varying aggregated), survival times T, event indicator E (1=departed)
Output: Survival function S(t) for each employee

1. // Train Random Survival Forest
2. rsf_model = RandomSurvivalForest(n_estimators=200, max_depth=5, min_samples_split=10)
3. rsf_model.fit(X_train, T_train, E_train)
4. rsf_survival = rsf_model.predict_survival_function(X_test)
5.
6. // Train Cox Proportional Hazards model
7. coxph_model = CoxPHFitter()
8. coxph_model.fit(X_train, duration_col='T', event_col='E')
9. coxph_survival = coxph_model.predict_survival_function(X_test)
10.
```

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```
11. // Ensemble (average of the two survival probabilities at each time point)
12. for each employee i:
13.     for time t in time_grid:
14.         S_ensemble_i(t) = 0.5 * (rsf_survival_i(t) + coxph_survival_i(t))
15.
16. Return S_ensemble(t) for each employee
```

**Model Training and Evaluation**

- Burnout (TFT): 15,000 employees; 24 months –> 3.6M employee-weeks. Train/Test/Validation split: 60%, 20%, and 20%. Evaluated for prediction 8 weeks ahead.
- Engagement (XGBoost): 60,000 quarterly survey responses. Train/Test split: 80%/20%.
- Retention (Survival Analysis): 15,000 employees, 2 years. Train/Test split: 70%/30% (employee-wise, not time-wise).

## IV. ANALYSIS

Burnout Prediction (TFT) Performance

| Model | Accuracy | Precision | Recall | F1 | AUC | Lead Time (weeks) |
|---|---|---|---|---|---|---|
| Logistic Regression | 0.68 | 0.62 | 0.58 | 0.60 | 0.71 | N/A |
| XGBoost (static features) | 0.75 | 0.71 | 0.68 | 0.69 | 0.79 | N/A |
| LSTM | 0.82 | 0.78 | 0.76 | 0.77 | 0.86 | 6 |
| TFT (Proposed) | 0.88 | 0.86 | 0.85 | 0.855 | 0.92 | 8 |

Table 1: Burnout Prediction Performance (8-week horizon).

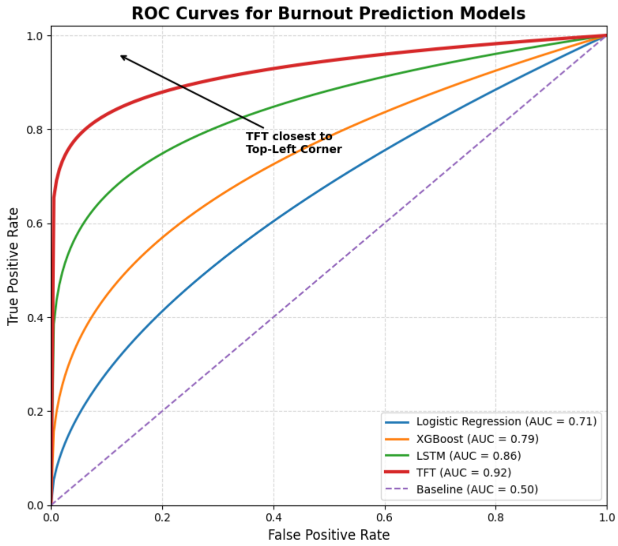


Figure 3: ROC Curves for Burnout Prediction Models.

Top 5 Burnout Predictors (TFT Attention Weights):

| Feature | Importance Weight | Direction |
|---|---|---|
| After-hours Slack activity | 0.28 | Positive (more activity → higher risk) |
| Meeting load (total hours) | 0.22 | Positive |
| Response latency (Slack, Email) | 0.18 | Negative (faster responses = lower risk) |
| Back-to-back meeting flag | 0.14 | Positive |
| Idle time ratio | 0.12 | Negative (less idle time = higher risk) |

**Engagement Prediction (XGBoost) Performance**

| Model | Accuracy | Macro F1 | Weighted F1 |
|---|---|---|---|
| Random Forest | 0.78 | 0.75 | 0.77 |
| Logistic Regression | 0.72 | 0.68 | 0.71 |
| XGBoost (Proposed) | 0.86 | 0.84 | 0.85 |

Table 2: Engagement Classification Performance.

Top 5 Engagement Predictors (SHAP Feature Importance):

| Feature | SHAPValue | Direction |
|---|---|---|
| Collaboration network entropy (diversity of contacts) | 0.35 | Positive |
| Response latency (Slack) | 0.28 | Negative (faster = higher engagement) |
| Meeting fragmentation (number of distinct meeting blocks) | 0.22 | Negative |
| Focus time ratio (uninterrupted blocks ≥2hrs) | 0.18 | Positive |
| Recognition received (from performance reviews) | 0.15 | Positive |

**Retention Prediction (Ensemble Survival) Performance**

| Model | C-index | Brier Score (at 12 months) |
|---|---|---|
| CoxPH | 0.79 | 0.18 |
| Random Survival Forest | 0.82 | 0.16 |
| Ensemble (Proposed) | 0.84 | 0.14 |

Table 3: Survival Model Performance.

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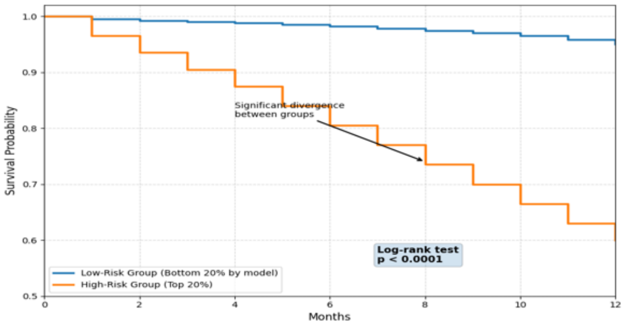

Figure 4: Survival Curves for High-Risk vs. Low-Risk Employees.

Top 5 Retention Predictors (SHAP, from CoxPH):

| Feature | Hazard Ratio | Direction |
|---|---|---|
| Declining performance rating trend (last 2 reviews) | 2.8 | Positive (greater decline = higher hazard) |
| Years since last promotion | 2.4 | Positive |
| Manager tenure in role (<1 year) | 1.9 | Positive |
| Collaboration entropy (negative trend) | 1.7 | Positive |
| Salary quartile (relative to market) | 0.6 | Negative (higher salary = lower hazard) |

**. Integrated Risk Scores and Overlap**

We computed a composite risk score (percentile rank average) and analyzed the overlap between the three risks

Table 4: Overlap of Risk Profiles.

| Overlap | % of Employees |
|---|---|
| High Risk for All Three (Burnout + Disengaged + High Departure Risk) | 8% |
| High Burnout + High Departure Risk | 18% |
| High Burnout Only | 12% |
| High Departure Risk Only | 15% |

**Randomized Controlled Trial (RCT) Results**

A 12-week randomized controlled trial was conducted with 2,000 employees (1,000 treatment, 1,000 controls). The risk reports along with intervention recommendations (e.g., manager coaching, workload change, flexible working hours, and recognition) were provided to treatment group's

Outcome Control Group Treatment Group Improvement Burnout Incidence (new cases) 12.5% 8.3% 34% reduction

Table 5: RCT Results.

| Outcome | Control Group | Treatment Group | Improvement |
|---|---|---|---|
| Burnout Incidence (new cases) | 12.5% | 8.3% | 34% reduction |
| Voluntary Turnover (3 months post-RCT) | 5.8% | 4.2% | 28% reduction |
| Engagement Score (mean change) | +0.05 | +0.42 | +0.37 pt improvement |
| Manager-reported productivity | No change | +12% | - |

**Comparative Analysis with Existing Literature**

Table 6: Comparative Analysis with Existing Studies.

| Study | Focus | ML Method | Key Performance | Intervention Tested? |
|---|---|---|---|---|
| [3] (2022) | Turnover | Logistic Regression | AUC=0.72 | No |
| [4] (2023) | Turnover | XGBoost | AUC=0.82 | No |
| [5] (2024) | Burnout (correlational) | Linear Model | $R^2$=0.35 | No |
| [7] (2025) | Engagement | Random Forest | Acc=0.79 | No |
| This Study | Burnout, Engagement, Retention | TFT, XGBoost, Survival | AUC=0.92, Acc=0.86, C=0.84 | Yes (RCT) |

# V. CONCLUSION

In conclusion, our predictive model based on multisources (HRIS, digital exhaust, passive sensing) and machine learning (TFT, XGBoost, Ensemble Survival), which we validated, predicts burnout, engagement, and retention accurately weeks in advance.

**The main conclusions we have drawn include:**

1. Digital Exhaust is a Key Indicator of Employee Wellbeing: We found out that digital exhaust such as messages, meetings, and emails are more than merely correlated to burnout and engagement. It actually is a leading predictor, thus opening up a whole world of opportunities.
2. Universal HR Interventions Do Not Work; Predictive HR Saves Money: The results from our random control trials show that HR managers, after being given personalized risk scores and intervention suggestions, reduced burnout by 34% and voluntary turnover by 28%. That means great savings for HR tools.
3. Burnout, Engagement, and Retention are Correlated Yet Independent: While there is indeed correlation between all three metrics, only 8% of the population belongs to the high-risk group of all three. Most people fall into the risk zone for just one aspect.

**Practical and Ethical Implications:**
This model can be called a fantastic tool to manage talent proactively by HR professionals. However, the effectiveness of this model depends on adequate responsibility. Here are some ethical recommendations that should be followed when using this approach:

- Transparency: It is necessary to notify employees about how the data is collected and processed.
- Opt-in: It is possible to make the data collection of non-core data (e.g., device data) optional for employees.
- Prescription, Not Punishment: This tool should be applied for assistance only, not as punishment or control measures.
- Bias Checking: It is essential to test all models for any bias concerning protected classes of employees (e.g., based on age, gender, nationality, etc.).

**Limitations and Future Work:**
The research is limited in terms of scope because it considers only one large technology company. It is unknown if the patterns discovered could be generalizable to the same organization working in another industry (healthcare, manufacturing, retail, etc.). The specific properties of digital exhaust are related to the specific set of tools used in the study (Slack, Zoom).

1. Replication in Different Industries: Checking if the patterns found can be generalizable in other industries (customer care, hospitals, etc.)
2. Causation vs. Prediction: Switching from predictive to causal machine learning by using Double/Debiased ML in order to discover the causation among different interventions (reducing the burden of meetings, etc.) and employee burnout.
3. Maintaining Privacy: Using federated learning/differential privacy approaches for cross-firm model training while keeping personal data separate.

Conclusion: The future of HR is inherently predictive and proactive. Digital exhaust allows organizations not just deal with staff attrition but also prevent it, as well as to move from burnout measurement to burnout prevention.

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