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Predictive Analytics for Employee Attrition: Integrating Organizational and Behavioral Data

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Abstract

Voluntary attrition is costly, yet most attrition models in use rely on static organisational records such as tenure, pay and promotion history. This paper examines the incremental predictive value of behavioural signals, including engagement survey scores, declining system activity, absence counts and collaboration intensity, when they are integrated with organisational data. A simulation harness generates a workforce of 4,000 employees from a logistic data-generating process in which attrition depends on both classes of predictor, and three learners (logistic regression, random forest and gradient boosting) are trained on organisational features alone and on the integrated feature set. On a held-out sample, the area under the ROC curve rises from 0.59–0.62 with organisational features alone to 0.77–0.78 with the integrated set, average precision almost doubles, and the Brier score falls from 0.16 to 0.13. Permutation importance attributes the largest share of discriminative power to engagement and to the trend in system activity. The paper translates these findings into a data-integration architecture, a governance checklist for behavioural monitoring and a decision rule for targeting retention interventions. The study's contribution is a transparent, reproducible demonstration of the conditions under which behavioural integration pays off and of the ethical constraints that must accompany it.

Keywords: employee attrition; turnover prediction; people analytics; behavioural data; gradient boosting; human resource analytics.

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Introduction

Replacing an employee who leaves voluntarily typically costs between one-third and twice the departing employee's annual salary once recruitment, onboarding, lost productivity and knowledge loss are counted. Human resource (HR) functions have therefore invested in predictive attrition models that score each employee's probability of leaving within a planning horizon, so that managers can intervene selectively. The theoretical basis for such models is long established: turnover unfolds through a sequence of withdrawal cognitions and behaviours before the decision to quit is executed [1], [2], and organisational conditions such as pay equity, promotion opportunity and workload shape those cognitions [3].

In practice, most deployed models draw almost exclusively on the organisational records held in the human capital management system: tenure, salary relative to market, time since last promotion, overtime flags and performance ratings. These variables are reliable and readily available, but they change slowly and describe the employee's situation rather than the employee's response to it. The withdrawal process, by contrast, leaves behavioural traces, such as declining engagement scores, reduced system activity, rising absence and shrinking collaboration networks, which are observable months before resignation. Whether these traces add predictive value beyond organisational data, and by how much, is the central question of this paper.

Because behavioural data are sensitive and their collection raises legitimate concerns about surveillance, the question cannot be answered responsibly by simply pooling whatever data are at hand. This study instead uses a simulation harness in which the data-generating process is explicit, the relative contributions of organisational and behavioural predictors are known, and the incremental value of integration can be measured cleanly. The findings are then used to derive design and governance recommendations for organisations considering behavioural integration.

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Background and Related Work

Turnover theory

Mobley's intermediate-linkages model describes turnover as a chain running from dissatisfaction through thoughts of quitting, search intentions and evaluation of alternatives to the decision to leave [1]. Later work emphasised that many departures follow shocks, that is, discrete events that prompt re-evaluation, rather than gradual dissatisfaction [2]. Both perspectives imply that observable behaviour changes before departure, which is the premise of behavioural attrition analytics. At the collective level, turnover also degrades unit performance and raises the attrition risk of remaining colleagues [4], which strengthens the case for early intervention.

Predictive attrition modelling

Early attrition models used logistic regression on demographic and job variables. Tree ensembles, including random forests [5] and gradient boosting [6], have since become standard because they capture interactions, such as the combination of long tenure without promotion and below-market pay, without manual specification. Evaluation conventionally uses the area under the ROC curve (AUC) [7]; because attrition is a minority class, average precision and calibration measures such as the Brier score are also informative.

Behavioural data and governance

Engagement surveys, collaboration metadata and system-usage logs are now routinely collected, and people-analytics teams increasingly combine them with HR records [8]. The ethical and legal considerations are substantial: inferences about an individual's intention to leave can be misused, and monitoring can itself damage trust. Interpretable modelling, in which the drivers of a score can be inspected and challenged [9], [10], is therefore a prerequisite for responsible deployment.

Methodology

Data-generating process

The harness simulates $N = 4{,}000$ employees. Five organisational variables are drawn: tenure in years (exponential, mean 4), salary relative to market (normal, mean 1.00, SD 0.15), years since last promotion (exponential, mean 3), an overtime indicator (Bernoulli, $p = 0.30$) and manager rating (normal, mean 3.5, SD 0.7). Four behavioural variables are drawn: a standardised engagement score, a standardised index of declining system activity that is negatively correlated with engagement, a count of absences (Poisson with rate rising as engagement falls) and a standardised collaboration index positively correlated with engagement. Attrition within the planning horizon follows a logistic model,

$$\operatorname{logit} P(A = 1) = \beta_0 + \beta_{org}{}^{T} x_{org} + \beta_{beh}{}^{T} x_{beh}, \quad (1)$$

with coefficients chosen so that tenure, salary ratio, manager rating, engagement and collaboration reduce attrition risk, and promotion gap, overtime, declining activity and absences raise it. The intercept yields a realised attrition rate of 19.8%. The coefficients are fixed design parameters rather than estimates, and all draws use a fixed random seed.

Learners and feature sets

Three learners are compared: logistic regression with standardised inputs, a random forest with 400 trees and minimum leaf size of 5, and gradient boosting with default depth-3 trees. Each learner is trained twice, once on the five organisational variables only and once on the integrated set of nine variables. The sample is split 70/30 into training and hold-out sets with stratification on the outcome. Implementation uses scikit-learn [11].

Evaluation and interpretation

Performance on the hold-out set is reported as AUC, average precision (AP) and Brier score. Variable contributions are estimated by permutation importance [12], defined as the mean decrease in AUC when a variable is randomly permuted in the hold-out set, averaged over ten repetitions. Because permutation importance measures reliance by the fitted model rather than causal effect, it is used only to characterise the model's behaviour.

Results

Incremental value of behavioural integration

Table 1 reports hold-out performance. With organisational features alone, discrimination is weak: AUC lies between 0.59 and 0.62 and AP between 0.25 and 0.28, only modestly above the 0.20 base rate. Adding behavioural features raises AUC to 0.77–0.78 and AP to 0.51–0.53 for every learner, and lowers the Brier score from roughly 0.16 to 0.13. The improvement is consistent across learners and larger than the differences between learners; in this setting the choice of data matters far more than the choice of algorithm. Logistic regression performs on a par with the ensembles because the data-generating process is additive on the logit scale, so the ensembles' capacity to represent interactions confers no advantage.

Which signals carry the information?

Figure 1 shows permutation importance for the gradient-boosting model trained on the integrated set. Engagement dominates, with a mean AUC decrease of 0.096 when permuted. The decline-in-activity index (0.028) and collaboration index (0.027) follow, and tenure (0.024) is the most informative organisational variable. Overtime (0.016) and salary ratio (0.014) contribute modestly, while promotion gap, manager rating and absence count contribute little once the other variables are present. Three of the four most important variables are behavioural, which explains the size of the gain in Table 1.

Table 1: Hold-out performance by learner and feature set (synthetic workforce, $N = 4{,}000$, attrition rate 19.8%)

Learner	*Feature set*	*AUC*	*Average precision*	*Brier score*
Logistic regression	Organisational only	0.616	0.275	0.156
Random forest	Organisational only	0.586	0.252	0.163
Gradient boosting	Organisational only	0.598	0.270	0.159
Logistic regression	Organisational + behavioural	0.781	0.530	0.128
Random forest	Organisational + behavioural	0.773	0.509	0.130
Gradient boosting	Organisational + behavioural	0.774	0.527	0.129

Operational interpretation

At the base rate of 19.8%, a model with AP of 0.53 means that, averaged over operating points, more than half of the employees flagged are genuine leavers, compared with roughly one in four for the organisational-only model. For an HR team with capacity to hold structured retention conversations with 10% of the workforce, this difference translates directly into the number of at-risk employees reached per unit of managerial time.

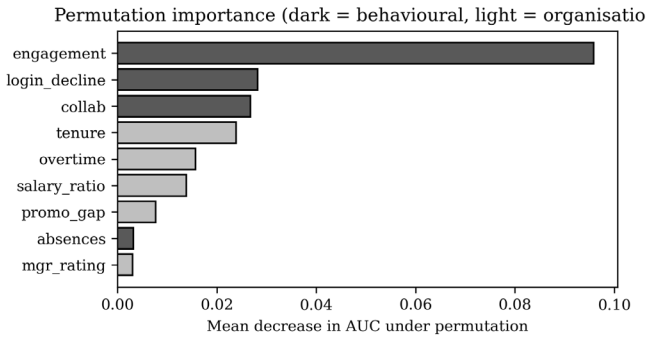


Figure 1: Permutation importance of organisational and behavioural variables in the integrated gradient-boosting model

Discussion and Implications

A data-integration architecture

The results motivate a three-layer architecture. The first layer is the system of record, which supplies organisational features at monthly granularity. The second is a behavioural feature store that converts raw survey, activity and collaboration data into aggregated, time-windowed indicators such as the slope of activity over the last 90 days, in line with the trend-based signals that proved informative here. The third is a scoring and explanation service that produces calibrated probabilities together with per-employee attributions, so that managers see why a score is high before acting on it.

From score to intervention

A high attrition score is useful only if it changes a decision. Recent evidence shows that targeting the highest-risk individuals is not always the most effective retention policy, because some high-risk employees are unresponsive to intervention [13]. The score should therefore be combined with an estimate of intervention responsiveness, and the targeting rule should prioritise employees with both elevated risk and plausible responsiveness. Behavioural signals support this refinement: an employee whose engagement has fallen after a specific shock may respond to a conversation about that shock, whereas one whose activity has been declining for a year may already have decided to leave.

Governance of behavioural monitoring

Because engagement and activity signals carry the most information, organisations will be tempted to collect them at fine granularity. Four safeguards are recommended. Aggregation: use windowed trends rather than raw event logs, which preserves most of the signal while reducing intrusiveness. Transparency: disclose which data are used and for what purpose, and allow employees to see their own indicators. Purpose limitation: restrict the use of attrition scores to retention support, with explicit prohibition on their use in promotion or termination decisions. Interpretability: prefer models whose attributions can be audited [9], and log every intervention triggered by a score so that its fairness and effectiveness can be reviewed.

Theoretical contribution

The simulation demonstrates a general principle for people analytics: when the outcome is driven by a process that manifests in behaviour before it manifests in records, the marginal value of behavioural data exceeds the marginal value of algorithmic sophistication. This reframes the analytics investment decision away from model selection and toward data governance and feature design, consistent with the withdrawal-process view of turnover [1], [2].

Limitations

The harness assumes that behavioural variables are measured without systematic bias and that their relationship with attrition is additive and stable. Real behavioural data are noisier, exhibit seasonal and role-specific patterns, and may change once employees know they are monitored. The learners use default hyperparameters, and the sample is cross-sectional rather than longitudinal. The magnitudes reported should therefore be read as illustrations of the

integration effect under a known process, not as benchmarks for any particular organisation. Replication on field data, with attention to temporal validation and fairness auditing across demographic groups, is the necessary next step.

Conclusion

Integrating behavioural signals with organisational records raised attrition prediction from barely informative to operationally useful in a controlled simulation, with AUC improving by about 0.17 and average precision nearly doubling, while the choice of learner made little difference. Engagement and activity trends carried most of the gain. The practical recommendations are to invest in a governed behavioural feature store, to couple risk scores with responsiveness estimates when targeting interventions, and to adopt explicit safeguards on data use. The harness is reproducible and can be re-parameterised to explore other assumptions about the attrition process.

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