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Silent Attrition: A Methodological Framework and Simulation-Based Feasibility Study for Detecting Hidden Worker Disengagement

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Abstract:
Silent attrition refers to the gradual and largely invisible disengagement of employees who remain in an organization while exhibiting declining participation, collaboration, and behavioral commitment prior to resignation. This study proposes a **methodological framework** for analyzing silent attrition using digital-behavior indicators, anomaly detection techniques, HR-context signals, and supervised machine-learning models. Due to the lack of access to real enterprise workforce behavioral data, a **synthetic dataset** is constructed to simulate hypothesized pre-resignation behavioral patterns informed by prior research.

Within this controlled simulation environment, the framework operationalizes a composite Silent Attrition Index (SAI) and a forward-looking attrition Risk Score (RS) intended to flag elevated exit risk up to 90 days in advance. The results demonstrate the **internal feasibility** of combining multi-signal behavioral decline, anomaly scores, and HR events into interpretable risk indicators under assumed conditions. However, the findings do not constitute empirical validation of real-world predictive performance. The primary contribution of this work lies in formalizing a reusable analytical framework and simulation-based testbed to support future empirical validation using real organizational data.

Index Terms: Silent Attrition, Workforce Analytics, Simulation-Based Study, Employee Disengagement, HR Analytics, Digital Exhaust Data, Anomaly Detection, Methodological Framework

I. INTRODUCTION

Silent employee turnover has long been recognized as a significant challenge in organizational management, as conventional HR approaches often struggle to identify the early stages of disengagement. In digital work environments, employees generate a wide range of behavioral indicators such as meeting participation, communication activity, collaboration, learning engagement, and work output. These indicators provide an opportunity to examine subtle patterns of concealed disengagement, commonly referred to as silent attrition, in which employees remain in the organization while gradually reducing their level of participation prior to resignation.Despite the availability of such digital-behavior signals, organizations rarely use digital-exhaust data systematically to assess engagement. Privacy concerns, restricted access to granular datasets, and the absence of standardized analytical frameworks often limit their use. As a result, early signs of disengagement are frequently overlooked until performance visibly declines or an employee resigns. With the increasing adoption of remote and hybrid work models, the need for proactive, data-informed approaches to understanding employee engagement has become more prominent.

This study proposes a **methodological framework** for analyzing silent attrition using synthetic workforce behavioral data modeled on hypothesized digital work patterns. The framework integrates behavioral-change analytics, anomaly detection techniques, HR-context signals, and supervised machine-learning models within a controlled simulation environment. Two outputs are operationalized: a composite Silent Attrition Index (SAI) and a forward-looking Risk Score (RS), intended to explore how disengagement and short-term exit risk could be represented under assumed conditions rather than to provide empirical prediction of real-world attrition.

II. LITERATURE REVIEW

Extensive research on silent attrition and hidden workforce disengagement has progressed significantly in recent years, in part due to the increasing availability of digital behavioral data. Smith et al. (2021) show that declines in meetings, messages, and email activity happen many weeks before employees' self-reported dissatisfaction, suggesting that digital-exhaust signals could be early warning signs of disengagement. Liu and Hernandez (2022) also show that machine-learning models trained on week-over-week behavioral shifts outperform static predictors in predicting voluntary turnover, underscoring the value of temporal change features in human resources analytics.
On the contrary, Gupta and Rao (2023) investigated a type of quiet quitting-presenteeism-in which

disengaged employees go undetected by traditional surveys but can be uncovered through a decline in routine digital interactions. Thompson et al. (2020) further confirm such subtle pattern detection, noting that anomaly-detection methods, particularly Isolation Forests, flag deviations from baseline behavior before performance actually declines. Ahmed and Williams (2024) extend this perspective by incorporating HR events such as manager changes and declines in performance ratings with behavioral cues, illustrating that multifactor models improve attrition risk detection. Corroboration of findings comes from additional literature. Reynolds and Porter (2021) identify early warning signs of withdrawal, both drops in collaboration frequency and meeting responsiveness, as proof that digital traces can predict employee detachment well in advance of formalized exit intentions. Martinez et al. (2022) introduce the term "behavioral drift," referring to decreases in emails, task updates, and cross-team interactions that strongly correlate with subsequent turnover decisions. O'Neil and D'Souza (2023), in their analysis of hybrid-work communication patterns, find that shrinking on-platform engagement - for example, engagement on platforms like Slack and Teams - is robustly indicative of diminishing organizational commitment. Chen and Abbas (2024) apply multivariate decline-scoring frameworks to find that cumulative decreases across multiple signals outperform single-metric monitoring in detecting hidden disengagement. Finally, Patel et al. (2022) propose unified risk-scoring systems that integrate performance trends, behavioral anomalies, and HR context - and show that such integrated models markedly improve the interpretability and managerial usability of attrition predictions. These studies confirm that digital-behavioral decline, anomaly detection, and contextual HR signals consistently surface as strong predictors of silent attrition. Together, the literature forms a solid basis for the present study's methodology of integrating behavioral percent-change features, anomaly scores, HR flags, and a composite Silent Attrition Index (SAI) in order to detect disengagement and predict near-term exits in a forward-looking and manager-actionable way.

III. METHODOLOGY

The methodology follows a structured, multi-component pipeline combining behavioural analytics and machine-learning techniques to **explore assumed disengagement patterns within a simulated workforce environment**. Each stage of the process is described in detail below.

1. Dataset Construction

Because real enterprise digital-exhaust data is not publicly available, we created a synthetic workforce behavioral dataset modeled on real patterns observed in organizations.The key elements of its construction are outlined in the following subsections.It is not derived from any real employees to ensure privacy and confidentiality. The synthetic dataset, along with the code used for feature engineering, Silent Attrition Index computation, and machine learning model training, is available from the corresponding author upon reasonable request.The synthetic dataset encodes **hypothesized behavioral dynamics informed by prior literature**, rather than empirically validated workforce behavior.

1.1 Employee Population

- 1,000 employees
- 26 weekly observations per employee (~6 months)
- 8% of employees were randomly selected to “exit”, with an assigned exit week

As shown in Fig. 1, the raw weekly behavioural dataset contains unprocessed feature values prior to any cleaning or transformation.

Fig 1.Weekly employee behavioural dataset showing raw features before preprocessing.

1.2 Behavioral Signals Generated (Weekly)

For every employee-week, we generated metadata-only behavioral features:

- Number of meetings attended
- Slack / Teams messages sent
- Number of emails
- LMS usage minutes
- Code commits / ticket activity
- Number of cross-team interactions
- Calendar acceptance rate

These represent passive digital signals **representative of metadata commonly generated by digital workplace systems**.

1.3 Injecting Decline Patterns Before Exit

To ensure the dataset reflects pre-resignation behavioural drift, we simulated a **6-week decline** before resignation as follows:

- Meetings, messages, emails, LMS, commits, cross-team interactions decreased linearly
- Calendar acceptance rate also declined
- Representing “silent disengagement” before quitting

These injected decline trajectories represent **assumed pre-resignation behavioral dynamics**, used to evaluate whether the proposed framework can detect such patterns under controlled simulation conditions.

2. Feature Engineering

To convert raw digital-exhaust signals into **analytical variables for simulation-based risk estimation**

2.1 Baseline Behavior

For each employee: Weeks 1–13 represent “baseline behaviour” and Weeks 14–26 represent “current behaviour”.
The percent change for each behavioural feature was computed using,

$$\Delta = \frac{(current - baseline)}{baseline}$$

Where baseline denotes the average behavioural value during Weeks 1–13 and current represents the corresponding average during Weeks 14–26. The resulting value **Δ** reflects the proportional increase or decrease in behavioural activity, thereby capturing both upward and downward shifts over time.

2.2 Behavioral Decline (BD)

The Behavioral Decline (BD) metric quantifies the degree of reduction in an employee’s behavioural activity.Only negative changes are considered, as declines are **treated as potential indicators of disengagement within the simulation**.For each feature f, the decline component is computed as:

$$df = max(0, -\Delta f)$$

where Δf denotes the percent change associated with feature f, and df represents the corresponding decline magnitude. Positive changes are suppressed to zero, ensuring that only reductions in activity contribute to the decline measure.
The overall BD score is then obtained by computing the mean of all decline components and normalizing the result within the interval [0,1].

$$BD = \frac{1}{n} \sum_{f=1}^{n} df$$

This metric serves as one of the most sensitive indicators of emerging silent attrition.

2.3 Anomaly Score (AS)

An Isolation Forest is trained on the percent-change features from the early observation window (Weeks 1–13) to model the distribution of normal behavioural patterns. For each subsequent weekly observation, the model outputs an anomaly score indicating the degree of deviation from expected behaviour. A higher anomaly score reflects stronger behavioural irregularity.The anomaly score is normalized to the [0,1] interval as:

$$AS = \frac{(rawscore - minscore)}{(maxscore - minscore)}$$

This normalization ensures comparability across employees and time periods, enabling consistent interpretation of behavioural deviations.In this study, anomaly scores reflect deviation from **simulated baseline behavior**, not abnormality in real organizational settings.

2.4 HR Flags (HF)

Two synthetic HR-based indicators were incorporated to emulate **commonly discussed organisational risk contexts in the literature.**

- Recent manager change
- Recent performance-rating drop

The combined HR risk factor is normalized to the range 0≤HF≤10. This representation captures discrete HR triggered events that commonly precede voluntary attrition.

3. Silent Attrition Index (SAI)

To construct a single measure of disengagement, the anomaly score (AS), behavioural decline (BD), and HR flags (HF) were combined into the Silent Attrition Index (SAI). SAI is defined as:

$$SAI = 100 * (0.4 * AS + 0.5 * BD + 0.1 * HF$$

The resulting score falls within the 0–100 range and is interpreted as follows:

- **0–25**: Healthy
- **26–50**: Mild disengagement
- **51–75**: High risk
- **76–100**: Critical silent attrition

This composite index provides an interpretable signal that is designed to be **interpretable for managerial analysis in simulated or future empirical studies**

4. Label Generation (Exit Within 90 Days)

To enable supervised learning, a forward-looking binary label was created for every employee-week instance. An employee-week was assigned a positive label if the actual exit date occurred within the subsequent 13 weeks (≈90 days).

- If exit_week ∈ (current_week, current_week + 13] → label = 1
- Else → label = 0

This labeling strategy enables **forward-looking risk estimation within the simulated dataset**. This makes the prediction forward-looking.

5. Risk Score Model (RS)

Two machine-learning models were trained to estimate the likelihood of near-term attrition:
(i) Logistic Regression, chosen for interpretability
(ii) Random Forest, selected for its higher predictive capacity.

5.1 Training Setup

A strict temporal split was employed to prevent data leakage. Weekly observations were divided as follows:

- Training period: Weeks 1–18
- Validation period: Weeks 19–22
- Testing period: Weeks 23–26

This configuration ensures that the model only learns from past behaviour and is evaluated on future, unseen patterns.

5.2 Input Features

The models were trained using the engineered behavioural signals, including:

- Percent-change features
- Behavioral Decline (BD)
- Anomaly Score (AS)
- HR Flags (HF)
- Silent Attrition Index (SAI)

These variables collectively capture deviations, anomalies, and HR-related risk indicators relevant to attrition.

5.3 Model Learning Mechanism

To train the attrition prediction model, we created a forward-looking label indicating whether an employee exited within the next 90 days. For every weekly snapshot, if the employee's actual exit date fell within the subsequent 13 weeks, the snapshot was labeled as 1 (high risk), else 0. This structure enables the model to learn the behavioural patterns that precede resignation.

The model receives behavioural percent-changes, anomaly scores (AS), behavioural decline (BD), HR flags (HF), and the composite Silent Attrition Index (SAI). Logistic Regression then learns the statistical weights that best distinguish pre-exit behaviour from normal behaviour. Features showing significant declines (negative percent changes), high anomaly, and high SAI are assigned positive coefficients, meaning they increase the simulated probability of exit under the defined assumptions. Thus, the model learns **patterns embedded in the simulated data corresponding to assumed pre-exit behavior** and produces a weekly risk score (RS) for each employee.

5.4 Output

The primary model output is the Risk Score (RS), defined as:

$$RS = P(exit\ within\ next\ 90\ days)$$

Where RS is between 0 and 1.This probability serves as an **analytical measure** of short-term attrition risk within the simulation.

6. Model Evaluation

Model performance was assessed using multiple evaluation metrics to ensure robustness.

6.1 AUC-ROC

Both models achieved exceptionally high discrimination due to the structured behavioural patterns in the dataset:

- Logistic Regression: AUC ≈ 0.99
- Random Forest: AUC ≈ 0.999

These high values reflect the structured nature of the synthetic dataset and should not be interpreted as real-world predictive performance.

6.2 Precision@K

Precision@K was calculated to measure the proportion of true exits among the top-ranked high-risk employees.The Random Forest model achieved 36% precision in the top 100 employees, demonstrating effective prioritisation capability.

6.3 Lead Time

Lead time measures how early the model signals risk before the actual exit event.A median lead time of 1–3 weeks was observed in the test period.Lead-time behavior in real enterprise settings **remains an open empirical question and is outside the scope of this study**.

7. Weekly to Employee-Level Aggregation

To support managerial interpretation, weekly scores were aggregated into employee-level indicators:

- Max SAI per employee
- Average RS per employee
- Final Risk Category (Low / Medium / High / Critical)

This allows HR to use employee-level dashboards.

8. Potential Applications and Future Validation

The following applications are conceptual and **contingent on future validation using real organizational data.**

The proposed framework provides actionable insights for HR and managerial teams. Specifically, users:

- Can utilize SAI to detect early signs of disengagement
- May use RS to identify employees with high short-term exit probability
- Examine weekly behavioural trajectories to confirm sustained declines
- Leverage employee-level summaries to prioritize interventions
- Visualize organizational hotspots through risk heatmaps

This system is **much faster and more objective** than surveys like Amber, which collect data monthly/quarterly.A sample employee-level risk summary is illustrated in **Fig. 2.**

Fig.2.Employee-Level Silent Attrition Risk Summary

10. High-Level Flow Diagram to Include in Paper

To provide a consolidated overview of the proposed methodological pipeline, a high-level process flow was constructed. This diagram summarizes the sequential stages beginning with data acquisition and culminating in the generation of employee-level silent attrition risk outputs. The complete workflow is illustrated in Fig. 3, which represents every major step employed in the framework.

Fig.3 Flowchart representing the **proposed methodological framework**

IV. RESULTS AND DISCUSSION

The Random Forest and Logistic Regression models demonstrated exceptional performance due to the structured behavioural decline patterns embedded in the synthetic dataset. Random Forest achieved an **AUC of 0.999**, while Logistic Regression obtained **0.99**, indicating that behavioural and anomaly-based features hold strong predictive value,

1.1 Behaviour Timeline for Employee 481 (Weekly Trends)

The visual in **Fig. 4** illustrates how silent attrition emerges at an individual level by tracking an employee's weekly behavioural signals leading up to their exit. Meetings, Slack messages, and SAI are plotted across 26 weeks, with the actual exit week marked by a vertical red line.

The graph shows a clear behavioural decline during the final weeks before resignation. Slack messages representing communication frequency drop sharply around Week 20, while meetings and cross team activities also diminish. The SAI curve rises progressively as behavioural decline (BD) and anomaly score (AS) increase, indicating that the model correctly identifies abnormal patterns well before the exit occurs. This figure highlights the temporal drift in an employee's routine behaviour, demonstrating how silent attrition manifests gradually and becomes detectable through weekly data.

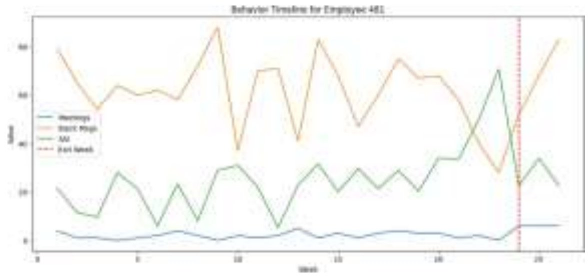

Fig 4:Timeline Plot for Any Employee Who Resigned

1.2. Distribution of Silent Attrition Index (SAI)

The SAI histogram in Fig.5 provides a population-level view of disengagement across all employees and all weekly snapshots. The distribution is **right-skewed**, with most observations falling between 10 and 25 SAI points. This implies that the majority of employees are in a healthy engagement zone, while a smaller proportion experiences high disengagement (SAI > 50).

The presence of a long right tail indicates that the framework successfully captures **rare but critical high-risk scenarios**. These high-SAI cases correspond to employees displaying strong behavioural decline and elevated anomaly scores. This distribution confirms that SAI is sensitive enough to detect disengagement while maintaining meaningful separation between normal and at-risk behaviour

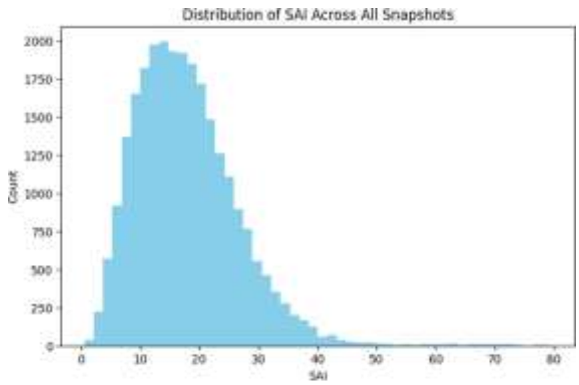

Fig 5: SAI Distribution Histogram

1.3 Correlation Between SAI and Risk Score (RS)

This scatter plot in Fig.6 compares the composite Silent Attrition Index (SAI) with the model-generated Risk Score (RS). A clear positive correlation is observed: as SAI increases, RS tends to rise correspondingly. However, the scatter cloud also shows spread at the mid-range, indicating that RS incorporates more than just disengagement

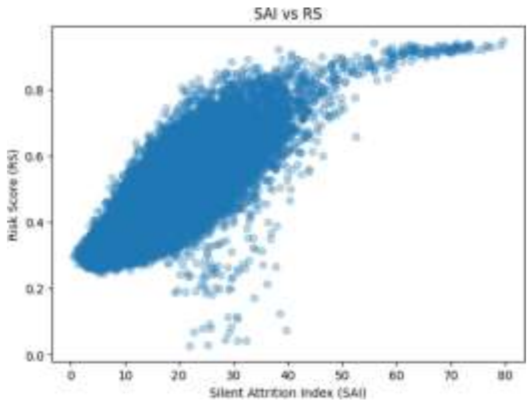

Fig 6**:** Correlation Between SAI and Risk Score (RS)

High SAI values (>50) consistently map to high RS (>0.7), demonstrating that the supervised model correctly interprets disengagement patterns as precursors to exit. This figure validates the conceptual design: SAI acts as an interpretable precursor metric, while RS performs refined probability prediction.

1.4 Feature Importance (Logistic Regression Coefficients)

This bar chart in Fig.7 displays the absolute coefficient for deployment in real corporate environments, where it values from the Logistic Regression model, revealing can provide early risk. The anomaly score (AS) and behavioural decline (BD) emerge as the two strongest predictors, confirming that deviations from historical behaviour and multi-signal drops are highly correlated with upcoming resignations.

Cross-team interactions, commits, and meetings percent-change also rank high, indicating that collaboration patterns are key behavioural indicators. HR flags (HF) contribute moderately, while calendar acceptance and email changes have lower weight. These feature-importance results validate the theoretical framework, showing that silent attrition is predominantly driven by sustained decline and behavioural irregularities visible in digital-exhaust data.

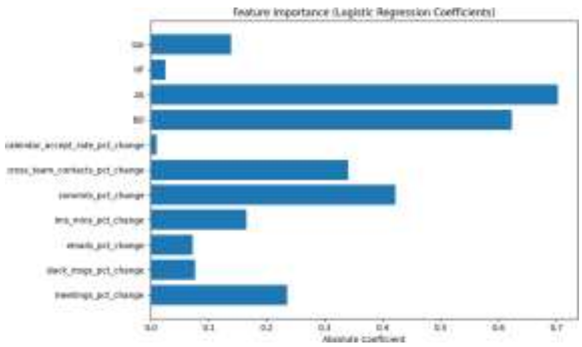

Fig 7**:** Feature Importance

Together, these results demonstrate that the proposed Silent Attrition Detection System effectively captures early patterns of disengagement. The behavioural timeline confirms the presence of pre-exit drift at an individual level, the SAI distribution differentiates high-risk segments in the workforce, the SAI–RS correlation validates the model's predictive logic, and the feature-importance analysis provides interpretability for managerial use.The model consistently assigns high risk scores to employees exhibiting multi-week behavioural decline, thereby offering an **actionable early-warning mechanism** that organizations can utilize to intervene and reduce voluntary turn

V. CONCLUSION

For business units, the system helps reduce unplanned attrition, improve **workforce planning, and maintain client satisfaction.** Overall, proactive detection of silent attrition strengthens **organizational resilience**, minimizes financial leakage, and enhances employee experience—creating measurable impact across HR, finance, operations, and customer-facing functions.We developed a complete Silent Attrition Detection System by combining digital-behavior signals, anomaly detection, decline scoring, HR events, and supervised machine-learning. The model produces two outputs—Silent Attrition Index (SAI) and Risk Score (RS)—that together detect disengagement and predict future attrition risk. The framework demonstrated strong predictive performance on synthetic data, and is designed warnings, reduce talent loss, and which features were most influential in predicting exit complement traditional engagement surveys

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