Cultural Pulse: Employee Sentiment Analysis of Employee Perceptions of Organisational Culture and Work Life Balance in Indian Corporates

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Abstract: *This study proposes CulturePulse, a hybrid Natural Language Processing (NLP) and Machine Learning (ML) framework for analysing employee sentiment towards organisational culture and work-life balance in Indian corporates. The study analyses 544 employee reviews collected from 26 companies using VADER-based sentiment scoring and workplace dimensions such as salary, culture, job security, work-life balance, and work satisfaction. Among the evaluated models, Logistic Regression achieved the highest performance with 94.95% accuracy and a 5-fold cross-validation score of 0.985. Findings indicate that work satisfaction is the strongest predictor of overall employee sentiment, while salary shows comparatively lower predictive influence despite frequent mention in reviews. The framework further identifies variations in employer brand strength and retention risk across firms.*
The study contributes a scalable NLP–ML framework for employee sentiment analytics and advances HR analytics research in the Indian corporate context.

Keywords: Employee Sentiment Analysis, Nlp, Machine Learning, Organisational Culture, Work-Life Balance, HR Analytics.

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Introduction

Employee sentiment analysis has emerged as a critical discipline within HR analytics, enabling organisations to move beyond periodic employee engagement surveys toward continuous, data-driven insight into workforce health (Ravichandran et al; 2023). In the Indian corporate context, where rapid economic growth coexists with high attrition rates, a talent market undergoing structural transformation, and a workforce that increasingly uses public review platforms to voice employment experiences, the need for robust computational approaches to understanding employee sentiment is urgent.

Publicly available employee review platforms such as AmbitionBox, Glassdoor, and LinkedIn have created an unprecedented corpus of authentic, unstructured employee voice data. These platforms allow employees to rate their organisations on multiple structured dimensions (salary, culture, work-life balance, job security, skill development, and work satisfaction) while simultaneously providing free-text reviews describing their experiences in their own words.

Despite growing interest in HR analytics in India, several gaps remain in the literature. First, general-purpose sentiment lexicons such as VADER were calibrated on Western social media text and have not been validated for Indian corporate review data, where cultural communication norms (Hall, 1976; Hofstede, 2001) tend to moderate negative language even when underlying experiences are deeply negative. Second, no large-scale empirical study has specifically tested whether the vocal dominance of salary complaints in Indian reviews corresponds to salary's actual predictive contribution to overall satisfaction. Third, the pay-to-stay hypothesis that above-market compensation reliably reduces voluntary attrition has rarely been empirically tested in the Indian corporate context.

The study addresses the gaps through the Culture Pulse framework: a hybrid NLP–ML pipeline applied to 544 employee reviews from 26 Indian companies. The framework integrates VADER compound sentiment scoring, six-dimensional workplace rating analysis, supervised machine learning classification (Logistic Regression, Random Forest, and Support Vector Machine), Pearson correlation driver analysis, attrition risk modelling, and a composite employer brand health monitor.

The structure of the paper is as follows: Section 2 reviews the relevant literature anchoring the six empirical signals that emerged from the analysis. Section 3 states the research objectives. Section 4 describes the methodology. Section 5 presents the findings. Section 6 discusses the implications of the findings, including limitations. Section 7 concludes with directions for future research.

Literature Review

2.1 Job Satisfaction Theory and the Driver Hierarchy

Herzberg, Mausner, and Snyderman's (1959) Two-Factor Theory provides the foundational framework for interpreting the driver hierarchy observed in this study. Herzberg distinguished between hygiene factors (external conditions) such as salary, working conditions, and job

security which prevent dissatisfaction but do not independently generate positive engagement, and motivators (intrinsic factors) such as meaningful work, recognition, and achievement that drive employee satisfaction. This distinction predicts that salary, while necessary to prevent discontent, will not be the dominant predictor of overall satisfaction (Choi et al; 2026); intrinsic dimensions such as work satisfaction and organisational culture should rank higher. The empirical findings in this study confirm this theoretical prediction at scale, using unstructured public review data rather than structured interview methodology.

Locke's (1976) facet satisfaction theory further predicts that satisfaction with the work itself including task identity, intrinsic motivation, and role-fit is the most proximal predictor of overall job satisfaction. Work Satisfaction's correlation of $r = 0.926$ with Overall Rating in the present study directly validates Locke's prediction in the Indian corporate context. Hackman and Oldham's (1975) Job Characteristics Model additionally identifies task significance, autonomy, and skill variety as central determinants of internal work motivation, providing a micro-level theoretical grounding for why work satisfaction's predictive power exceeds that of structural dimensions like salary.

2.2 Sentiment Analysis and Cultural Calibration

Hutto and Gilbert's (2014) VADER model was designed for English social media text short, informal, emotionally expressive, and produced predominantly by Western English-speaking users. The systematic upward bias observed in this study when VADER is applied to Indian corporate reviews is not a flaw in VADER's design; it is a deployment mismatch. Indian corporate reviews are written in a culturally distinct register: formal, hedged, two-field structured (Pros and Cons), and influenced by high-context communication norms (Hall, 1976) that suppress direct negative expression even when the underlying experience is deeply negative.

Nguyen, Shirai, and Velcin (2015) documented domain-specific vocabulary mismatches in sentiment analysis, where terms like 'hike' (salary increment) or 'band' (performance grade) carry distinct meanings in Indian corporate contexts. The present study extends that finding to a cultural-register mismatch that operates at a deeper level than vocabulary: the same words carry systematically different emotional loading in Indian corporate writing than in the corpora VADER was trained on. Raut, Narkhede, and Gardas (2021) applied sentiment classification to AmbitionBox reviews of Indian IT firms but did not document or correct for this calibration issue, making the hybrid model design in this study a direct methodological response to their approach.

Pang and Lee (2008) provide a comprehensive treatment of the trade-offs between lexicon-based and machine learning approaches to sentiment analysis. Kang et al. (2016) demonstrated empirically that models combining lexicon-based text scores with structured numerical ratings consistently outperform either input stream alone a finding that grounds the hybrid design choice in this study.

2.3 Compensation, Retention, and the Pay-to-Stay Hypothesis

The pay-to-stay hypothesis that above-market compensation reduces voluntary turnover has substantial academic support in Western labour market research (Lazear, 1981; Milgrom and Roberts, 1992). However, Hausknecht, Rodda, and Howard (2009) showed that compensation's protective effect on retention is conditional on baseline psychological safety, job security perception, and cultural alignment. When employees feel structurally insecure as is the case for Salesforce reviewers in this dataset following multiple global layoff cycles compensation operates as a recruitment inducement rather than a retention mechanism. Employees accept the salary premium while continuing passive job searching. This conditional model of compensation's retention effect is better captured by Adams's (1963) equity theory, which frames employee decisions as multi-dimensional comparisons of total experience against perceived alternatives.

2.4 Employer Branding and Brand Health Monitoring

Ambler and Barrow's (1996) employer branding framework identifies functional, psychological, and economic components of the employer value proposition. Lievens and Slaughter (2016) demonstrated that multi-source composite scores integrating objective ratings, sentiment distributions, and behavioural outcomes predict employer attractiveness better than single-source metrics. The composite Brand Health Score in this study operationalises all three components of Ambler and Barrow's framework: average overall rating (economic/functional), net sentiment ratio (psychological), and inverse attrition risk (behavioural). Moroko and Uncles (2008) emphasised consistency across touchpoints as a hallmark of successful employer brands; the uniformity of Apple's above-market performance across all six dimensions in this dataset confirms this consistency principle empirically.

2.5 People Analytics and the Analytics-to-Action Gap

Falletta (2014) identified the 'analytics-to-action gap' the structural disconnect between the availability of HR analytical capability and its translation into operational HR decision-making as the primary impediment to evidence-based HR practice. Bersin (2015) forecast that People Analytics would become a critical differentiator for organisations with advanced HR capability. The present study directly addresses the analytics-to-action gap by constructing a complete pipeline from raw public data to per-company, dimension-prioritised HR recommendations using exclusively open-source tools and publicly available AmbitionBox review data.

Research Objectives

The objectives of the study are as follows;

- **Objective 1** - Measurement Calibration: To develop and validate a hybrid NLP–ML sentiment scoring framework that corrects for the systematic underestimation of negative sentiment in Indian corporate employee reviews arising from cultural communication norms and general-purpose lexicon bias.
- **Objective 2** - Driver Reordering: To empirically establish the true relative importance of six workplace dimensions as predictors of overall employee satisfaction in the Indian corporate context, and to test whether salary holds the predictive dominance commonly assumed.

- **Objective 3** - Retention Economics: To examine whether compensation premium reduces attrition risk in Indian corporates, using the composite attrition risk model to test the pay-to-stay hypothesis across 26 companies.
- **Objective 4** - Prescriptive Analytics: To bridge the analytics-to-action gap by constructing a replicable employer brand health monitoring and dimension-prioritised HR recommendation system from publicly available review data.

Methodology

4.1 Data and Corpus Construction

The dataset consists of 544 employee reviews scraped from AmbitionBox, covering 26 companies across seven industry sectors: information technology (TCS, Infosys, Wipro, Accenture, Capgemini, IBM, Tech Mahindra), management consulting (BCG, Bain & Co., Deloitte, EY, PwC), aviation and aerospace (Airbus), construction and engineering (Galfar, Leighton Contractors), FMCG (Mondelez International), financial services (American Express, HDFC Bank, ICICI Bank), and technology and cloud platforms (Apple, Intel, Salesforce, Amazon, Flipkart, Reliance Industries, Tata Steel). Reviews were collected between 2023 and early 2026.

Each review contains two unstructured free-text fields (Pros and Cons) and seven structured numeric ratings scored on a 1–5 ordinal scale: Overall Rating, Salary, Company Culture, Job Security, Work-Life Balance, Skill Development, and Work Satisfaction. Post-cleaning including whitespace trimming, concatenation of Pros and Cons into a unified Review Text field, stop-word removal, lowercasing, and punctuation.

4.2 Text Preprocessing

All review text was lowercased, stripped of URLs, punctuation, digits, and extra whitespace using Python's re and string libraries. Pros and Cons fields were concatenated into a single Review Text field prior to sentiment scoring, consistent with VADER's design for single-document input. The resulting Clean Review field served as the input to the VADER sentiment analyser.

4.3 VADER Sentiment Scoring

Each clean review was scored using VADER (Valence Aware Dictionary and sentiment Reasoner; Hutto & Gilbert, 2014), producing positive, neutral, negative, and compound sub-scores. The compound score (range: −1.0 to +1.0) was used to classify reviews as text-positive (compound ≥ 0.05), text-negative (compound ≤ −0.05), or text-neutral. VADER classification was performed independently of all numeric ratings to permit divergence analysis between text-derived and rating-derived sentiment labels.

4.4 Actual Sentiment Labelling and Hybrid Scoring

Actual sentiment labels were derived from Overall Rating: ratings ≥ 3.5 were classified positive, ≤ 2.5 as negative, and intermediate values as neutral. The resulting class distribution 38.1% negative, 34.2% positive, 27.8% neutral represents mild imbalance. Stratified sampling in cross-validation ensured representative fold composition.

The hybrid sentiment score was computed as a weighted blend:

Hybrid Score = *(0.25 × VADER Compound) + (0.75 × Dimension Score)*

where Dimension Score is the mean of all sixdimensions ratings, linearly rescaled from [1, 5] to [−1, +1]. This 25:75 weighting reflects the stronger calibration reliability of structured numeric ratings relative to VADER scores in the Indian corporate context. Sentiment classification thresholds were set at Hybrid Score ≥ 0.425 (positive) and ≤ −0.225 (negative), with the remaining range classified neutral.

4.5 Machine Learning Classification

Three supervised classifiers were trained on the hybrid feature set using an 80/20 stratified train-test split: Logistic Regression (L2 regularization, C = 1.0), Random Forest (100 estimators, max_features = sqrt), and Support Vector Machine (RBF kernel, C = 1.0, gamma = scale). Features included all six dimension ratings plus the VADER compound score. The target variable was the three-class Actual Sentiment label. Model evaluation used held-out test accuracy, classification report (precision, recall, F1-score per class), and 5-fold stratified cross-validation (mean CV score and standard deviation as stability indicators). Feature scaling (StandardScaler) was applied prior to SVM and Logistic Regression training.

4.6 Key Driver Analysis

Pearson correlation coefficients were computed between each of the six workplace dimension ratings and the Overall Rating. Top-quartile lift analysis was conducted as a supplementary diagnostic: for each dimension, the mean Overall Rating was computed for reviews in the top quartile of that dimension, then divided by the dataset mean, yielding a lift multiplier. Variance Inflation Factor (VIF) analysis was conducted to assess multicollinearity among dimensions; several dimensions (notably Work Satisfaction and Culture) showed high inter-correlation, meaning regression coefficient magnitudes should be interpreted as directional signals rather than independent causal estimates.

4.7 Logistic Regression Coefficient Interpretation

Logistic Regression coefficient magnitudes were extracted and expressed as odds ratios (OR = exp(coefficient)) to quantify the directional contribution of each dimension to negative sentiment prediction. A one-unit increase in a dimension rating with a large negative coefficient corresponds to a proportionally large reduction in the odds of a negative sentiment prediction identifying that dimension as a high-leverage HR intervention point.

4.8 Attrition Risk Modelling

An attrition risk score was computed for each review as a composite of: (a) negative sentiment flag (binary, from predicted sentiment label), (b) inverse Overall Rating (linearly scaled to [0, 1]), and (c) count of dimension ratings below the dataset mean (scaled to [0, 1]). These components were averaged to produce a review-level Attrition Risk percentage. Risk bands were defined as Low (<35%), Medium (35–60%), and High (>60%). Company-level average attrition risk was aggregated from review-level scores.

4.9 Employer Brand Health Scoring

The composite Brand Health Score was constructed as:

Brand Health Score = *(0.40 × Normalized Average Overall Rating) + (0.30 × Net Sentiment Ratio) + (0.30 × Normalized Inverse Attrition Risk)*

Net Sentiment Ratio is the proportion of positive reviews minus the proportion of negative reviews. Company classification: Healthy (score ≥ 65), Stable (40–65), At Risk (<40). Weights reflect relative informational contribution: numeric rating as the primary signal, sentiment as the behavioural voice signal, and attrition risk as the forward-looking retention signal.

Results

5.1 Exploratory Data Analysis

The dataset's overall average rating is 3.09/5.00, placing the aggregate workforce experience marginally above neutral. The overall sentiment split 38.1% negative, 34.2% positive, 27.8% neutral — indicates that negative assessments outnumber positive assessments across the full corpus. This near-midpoint aggregate is consistent with what organisational psychologist term 'quiet dissatisfaction': employees continue to perform but carry elevated passive attrition risk and reduced discretionary effort.

VIF analysis confirmed high multicollinearity among the Work Satisfaction–Culture–WLB cluster. This does not invalidate the Pearson correlation analysis (which measures bivariate relationships independently) but requires that Logistic Regression coefficient magnitudes be treated as directional indicators rather than independent causal estimates.

5.2 ML Model Performance

Table 1 presents the full model comparison. Logistic Regression was selected as the primary classifier on three criteria: highest test accuracy (94.95%), lowest overfitting gap (3.2 percentage points between train and test, versus 8.0 for Random Forest), and highest cross-validation mean (0.985) with the lowest standard deviation (0.013). Logistic Regression's interpretability its coefficient magnitudes directly indicate which features most strongly predict negative sentiment — provides a practical advantage for HR diagnostics beyond predictive accuracy alone.

Model	Train Acc.	Test Acc.	CV Mean	CV Std
Logistic Regression	98.15%	94.95%	0.985	0.013
Random Forest	100.00%	91.97%	0.943	0.017
SVM (RBF Kernel)	96.30%	92.20%	0.972	0.02

Machine Learning Model Comparison — Accuracy, Cross-Validation, and Stability

Note. CV = 5-fold stratified cross-validation. Train accuracy of 100% for Random Forest confirms overfitting.

The overall hybrid VADER–ML model achieved 89.34% accuracy against rating-derived actual sentiment labels. The 10.66% residual error is substantially attributable to reviews where text and ratings conflict by design: reviewers who rate low but write diplomatically (a cultural pattern documented as high-context communication), or who rate high but vent specifically in the Cons field.

5.3 Key Driver Analysis

Table 2 presents the complete driver hierarchy with both Pearson correlation coefficients and top-quartile lift multipliers. Three features demand specific attention. First, the 18 correlation-point gap between Work Satisfaction (r = 0.926) and Salary (r = 0.744) is large enough to materially reorder any HR investment portfolio structured around complaint frequency. Second, VADER Compound score (r = 0.540) is the weakest predictor of all weaker than every structured dimension confirming that text sentiment alone is an inadequate proxy for overall employee experience in this corpus. Third, Company Culture achieves the highest top-quartile lift (3.07×), meaning employees who rate culture highly show an over-three-times uplift in overall rating the largest single-dimension multiplier in the dataset.

Rank	Dimension	Pearson r	Top-Q Lift	Diagnostic Implication
1	**Work Satisfaction**	0.926	2.80×	Most powerful lever; lowest avg rating (2.92/5)
2	**Company Culture**	0.909	3.07×	Highest top-quartile lift; universal differentiator
3	**Skill Development**	0.876	2.80×	Stable dimension; rarely a crisis trigger
4	**Work-Life Balance**	0.863	2.90×	Most visible in negative text; structural in consulting
5	**Job Security**	0.81	2.86×	Critical post-layoff signal (Salesforce, Intel)
6	**Salary**	0.744	2.04×	Loudest complaint; weakest predictor — Herzberg confirmed

Key Driver Analysis — Pearson Correlation and Top-Quartile Lift Against Overall Rating

Note. VADER Compound Score (r = 0.540, lift = 1.73×) is included for comparison but is not a workplace dimension.

5.4 Workplace Dimension Sentiment Distribution

Table 3 presents dimension-level average ratings and sentiment distributions. Work Satisfaction is the only dimension where negative assessments match or exceed positive assessments in proportion (41.4% negative vs. 41.2% positive) a near-symmetrical split reflecting deep structural dissatisfaction at the level of day-to-day role fulfilment. Skill Development is the most stable dimension relatively high mean, relatively low negative proportion suggesting that most organisations invest enough in learning infrastructure to prevent extreme dissatisfaction, even if they do not use it as a strategic differentiator.

Dimension	Avg Rating	Positive%	Neutral%	Negative%	Status
Work Satisfaction	2.92	41.20%	17.50%	41.40%	Weakest
Salary	3.11	43.40%	21.70%	34.90%	Paradox
Company Culture	3.11	46.30%	16.50%	37.10%	Wide variance
Work-Life Balance	3.11	45.60%	17.30%	37.10%	Consulting risk
Job Security	3.13	47.80%	17.50%	34.70%	Layoff-sensitive
Skill Development	3.17	48.00%	18.00%	34.00%	Most stable

Workplace Dimension Sentiment Summary — Dataset-Level Averages and DistributionsNote. All ratings are on a 1–5 ordinal scale. Positive/Neutral/Negative % are computed from reviewer-assigned dimension ratings.

5.5 Logistic Regression Coefficient Analysis

Table 4 presents the negative sentiment odds ratios derived from the Logistic Regression model. All coefficients are negative, confirming that higher ratings on every dimension reduce the odds of a negative sentiment prediction. The Work Satisfaction coefficient (−2.228, OR = 0.108) means that a one-unit increase in Work Satisfaction reduces the odds of a negative sentiment prediction by approximately 89% the largest marginal effect. The Salary coefficient (−1.428, OR = 0.240) has the smallest effect consistent with its position as the weakest driver in the Pearson correlation analysis and with Herzberg's hygiene-factor model.

Feature	Coefficient	Odds Ratio	Interpretation
Work Satisfaction Rating	−2.228	0.108	Highest leverage: 1-unit increase cuts negative odds by ~89%
Company Culture Rating	−1.902	0.149	Culture & satisfaction co-move; second-most impactful
Job Security Rating	−1.820	0.162	Layoff-exposed companies carry elevated negative risk
Work-Life Balance Rating	−1.801	0.165	Structural in consulting; fast responder to WLB policy change
Skill Development Rating	−1.756	0.173	Moderately impactful; table-stakes dimension
Salary Rating	−1.428	0.24	Smallest effect; confirms hygiene-factor role of pay

Logistic Regression Negative Sentiment Odds Ratios

Note. All coefficients negative; a higher dimension rating reduces negative sentiment odds. OR = exp(coefficient). High multicollinearity among dimensions means magnitudes are directional, not independently causal.

5.6 Employer Brand Health Monitor and Attrition Risk

Table 5 presents the full employer brand health rankings for all 26 companies (selected rows shown for the two Healthy, representative Stable, and all four At Risk companies). Apple leads with a Brand Health Score of 76.12 driven by the highest average overall rating (4.13), the largest positive net sentiment ratio (+63.2%), and the lowest average attrition risk (27.0%) in the dataset. Tech Mahindra sits at the floor (27.52), with 71.8% average attrition risk and only 4.8% positive review proportion. The four At Risk companies Salesforce, Accenture, PwC, and Tech Mahindra span three sectors (technology, professional services, and IT services), indicating that the risk pattern is not sector-specific.

The most analytically significant anomaly in Table 5 is Salesforce's at Risk classification (Brand Health Score: 44.48) despite carrying the highest average Salary Rating in the dataset (4.05/5). Salesforce's Job Security rating (2.29/5) and Culture rating (2.71/5) are the lowest among comparable technology firms in the dataset. Three rounds of global layoffs between 2022 and 2024 are directly cited in reviews, confirming that the compensation premium has not offset the psychological insecurity generated by structural job uncertainty. This is the clearest empirical falsification of the pay-to-stay hypothesis in the dataset.

Company	Avg Rating	Net Sentiment	Avg Attrition %	Brand Score	Band
Apple	4.13	63.20%	27.00%	76.12	Healthy
Intel	3.61	47.60%	36.50%	66.85	Healthy
American Express	3.45	27.30%	38.50%	63.84	Stable
Tata Steel	3.64	27.30%	36.60%	60.53	Stable
Reliance Industries	3.47	22.70%	35.80%	59.65	Stable
TCS	3.41	26.30%	43.60%	56.11	Stable
Wipro	3.09	0.00%	43.40%	55.66	Stable
EY	3.08	0.00%	44.80%	52.52	Stable
IBM	3.05	−4.5%	44.60%	52.38	Stable
Infosys	2.85	−14.3%	49.30%	51.62	Stable
BCG	3.1	−5.3%	47.40%	49.44	Stable
Deloitte	2.7	−18.2%	51.60%	45.43	Stable
Salesforce	2.9	−14.3%	52.30%	44.48	At Risk
Accenture	2.72	−22.7%	56.80%	42.54	At Risk
PwC	2.37	−50.0%	60.10%	36.28	At Risk
Tech Mahindra	1.93	−66.7%	71.80%	27.52	At Risk

Employer Brand Health Monitor — All 26 Companies (Selected Rows)

Note. Healthy ≥ 65 (green), Stable 40–65 (white/grey), At Risk <40 (red). Net Sentiment = positive% minus negative%. Brand Score = 0.40(avg rating) + 0.30(net sentiment) + 0.30(inverse attrition), all normalized.

Discussion

6.1 The Salary Paradox and Its HR Implications

The most practically consequential finding of this study is the 18 correlation-point gap between salary's linguistic salience in review text and its predictive contribution to overall satisfaction. Across 544 reviews, salary-related complaints 'no hike,' 'salary not matching market standards,' 'appraisal too low' dominate the negative word cloud and constitute the most frequently cited grievance category. Yet Pearson correlation analysis, top-quartile lift analysis, and Logistic Regression coefficient analysis converge on a consistent conclusion: salary is the weakest predictor of overall satisfaction among the six dimensions measured.

The implication is structural: HR functions that allocate budget in response to complaint frequency the most common decision heuristic are systematically misallocating resources away from the dimensions (Work Satisfaction, Culture, WLB) that actually move overall satisfaction. This finding validates Herzberg's Two-Factor Theory at scale in the Indian corporate context: salary functions as a hygiene factor, generating vocal complaints when deficient, but not generating proportionate engagement when improved. Work Satisfaction and Culture the motivator dimensions deliver the highest marginal return on overall satisfaction per unit of improvement.

6.2 VADER Cultural Calibration and the Hybrid Model

The 26–30% text-rating divergence rate documented in this study where VADER assigns neutral or positive compound scores to reviews with objectively low numeric ratings represents a systematic calibration failure rather than random error. The direction of divergence is consistently upward: VADER overestimates positivity in Indian corporate reviews because the reviewers moderate negative language in public-facing written formats, consistent with high-context communication norms (Hall, 1976; Hofstede, 2001) that suppress direct negative expression even when the underlying experience is deeply negative.

The practical consequence is significant: any HR analytics system relying solely on VADER text sentiment to assess Indian employee experience will misclassify approximately one in four employees, systematically under-flagging disengaged workers as neutral or satisfied. The hybrid model, by anchoring text sentiment to structured numeric dimension ratings, partially corrects this bias and achieves 89.34% overall accuracy. The remaining 10.66% error is attributable to the subset of reviews where text and ratings conflict by deliberate reviewer choice a limitation that a domain-specific Indian corporate sentiment lexicon could further reduce.

6.3 The Pay-to-Stay Falsification

Salesforce provides a clean natural experiment for testing the pay-to-stay hypothesis. With the highest average Salary Rating in the dataset (4.05/5), Salesforce would be predicted to show low attrition risk under a simple compensation-retention model. Instead, it shows 52.3% average attrition risk placing it in the at Risk brand health band. The mechanism is not ambiguous: collapsed Job Security (2.29/5) and Culture (2.71/5) ratings, directly linked by

reviewers to three rounds of global layoffs between 2022 and 2024, have generated psychological insecurity that compensation cannot offset.

This pattern — high compensation, elevated attrition risk appears across multiple firms in the dataset. BCG, Bain, and Deloitte all show above-average compensation paired with below-average brand health driven by Work-Life Balance and Job Security deficits. The consistent replication of this pattern across sectors (global technology, management consulting, professional services) rules out Salesforce as a sector-specific outlier. The finding aligns with Hausknecht et al.'s (2009) conditional model of compensation's retention effect: when employees feel structurally insecure, pay operates as a recruitment tool, not a retention mechanism.

6.4 Management Quality as the Universal Lever

The HR recommendation engine, applied independently to each of the 26 companies based on their specific dimension scores and attrition risk profiles, generated manager-related interventions for all 26 companies. Manager scorecards (26/26), stay interviews (22/26), anti-politics policies (15/26), and manager capability development (18/26) appear across every sector. This universality was not pre-specified; it emerged from algorithmic recommendation generation driven by each company's individual data profile. The word cloud analysis of negative reviews independently confirms the pattern: 'bad management,' 'politics,' 'toxic management,' and 'no appreciation' are the highest-frequency negative phrases across the full corpus.

This finding provides independent empirical confirmation of the Gallup manager effect that the immediate supervisor accounts for approximately 70% of variance in employee engagement scores (Harter et al., 2015) using three convergent methods: algorithmic recommendation output, word cloud frequency analysis, and Logistic Regression coefficient ranking (Work Satisfaction, most proximal to direct management experience, carries the largest coefficient magnitude). The convergence across methods strengthens the inference and its generalizability.

6.5 Limitations

Five limitations should be acknowledged. First, AmbitionBox reviewers are self-selected the most opinionated employees which skews sentiment distributions toward the tails relative to the broader workforce. The proportion of disengaged employees in the actual workforce may differ from what the review corpus suggests. Second, the dataset is cross-sectional: causal inference about what drives attrition risk is not warranted. Longitudinal tracking against actual voluntary turnover data would be required to validate the attrition risk model's predictive validity. Third, VADER cultural calibration is only partially corrected by the hybrid model; a fine-tuned Indian corporate sentiment lexicon remains an open need. Fourth, high multicollinearity among dimension ratings means Logistic Regression coefficient magnitudes should be read as directional signals, not independent causal estimates. Fifth, company-level review counts (14–23) are small; company-level statistics should be treated as directional indicators rather than statistically precise measurements.

Conclusion

This study presented CulturePulse: a hybrid NLP–ML framework for employee sentiment analysis in Indian corporates, applied to 544 reviews from 26 companies across seven sectors. The framework produced six empirically grounded findings that collectively challenge the most common assumptions in Indian HR analytics practice.

The central finding that Work Satisfaction (r = 0.926) is the strongest predictor of overall employee satisfaction while Salary (r = 0.744) is the weakest, despite salary's textual dominance in negative reviews has direct implications for how HR investment portfolios should be structured. Organisations that allocate budget in proportion to complaint frequency misallocate resources; organisations that allocate in proportion to driver strength invest where marginal returns are highest.

The hybrid NLP–ML architecture combining VADER compound scores with structured dimension ratings, validated by three ML classifiers and 5-fold cross-validation — provides a methodological template that is replicable, open-source compatible, and capable of monthly refresh on publicly available review data. The Employer Brand Health Monitor and attrition risk banding system translate quantitative findings into leadership-ready diagnostics without requiring proprietary data access or expensive survey infrastructure.

The most important practical finding of this study is structural rather than statistical: the technical infrastructure to continuously monitor employee sentiment at scale already exists, is publicly accessible, and is almost free to operate. The real constraint is most Indian companies lack a People Analytics function with the mandate, capability, and board-level support to operationalise such a system and act on its outputs at the speed the data permits.

The simplest and most important conclusion of this study is also the most actionable: employees' sense of meaningful, recognised, and fulfilling day-to-day work matters more than what they are paid. Building HR systems and investment decisions around that truth, rather than around the loudest complaint, is the practical work that remains.

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