

AI-AUGMENTED LEADERSHIP PROFILING: MACHINE LEARNING MODELS FOR IDENTIFYING TRANSFORMATIONAL AND ETHICAL LEADERSHIP TRAITS

RUBEENA MASUD

LECTURER, DEPARTMENT OF ENGLISH, JAZAN UNIVERSITY , TELANGANA, HYDERABAD EMAIL: Khursheedakhatoon24@gmail.com

SULAFA GEWI

LECTURER, DEPARTMENT OF ENGLISH, JAZAN UNIVERSITY, TELANGANA, HYDERABAD EMAIL: Khursheedakhatoon24@gmail.com

DR. KHURSHEEDA KHATOON

LECTURER, DEPARTMENT OF ENGLISH, HYDERABAD, TELANGANA, EMAIL: Khursheedakhatoon24@gmail.com

DR SHANKAR B B

ASSOCIATE PROFESSOR, NITTE (DEEMED TO BE UNIVERSITY), NMAM INSTITUTE OF TECHNOLOGY, DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING, NITTE, UDUPI DISTRICT, KARNATAKA 574110, INDIA, EMAIL: sankrubb@gmail.com

MR. V. ASOKKUMAR

SUSHIL DOHARE

ASSOCIATE PROFESSOR, PUBLIC HEALTH, COLLEGE OF NURSING AND HEALTH SCIENCES EMAIL - sdohare@jazanu.edu.sa

Abstract: Artificial intelligence has expanded the possibilities of leadership assessment by enabling objective, data-driven profiling that captures behavioural nuances far beyond traditional psychometric tools. This study proposes an AI-augmented framework for identifying transformational and ethical leadership traits using supervised machine learning models trained on multimodal organisational data, including communication patterns, decision-making logs, behavioural indicators, and validated leadership inventories. The research examines how algorithms such as Random Forest, Gradient Boosting, and Transformer-based language models can detect core dimensions of transformational leadership idealised influence, inspirational motivation, intellectual stimulation, and individualised consideration alongside ethical traits such as fairness, transparency, accountability, and moral judgement. A hybrid methodology is adopted, combining feature engineering, natural language processing, and model interpretability techniques to ensure transparency and bias mitigation. Results demonstrate that AI-generated leadership profiles improve predictive reliability, reduce evaluator subjectivity, and uncover hidden behavioural signatures that traditional assessments miss. The study emphasises the importance of explainability, ethical safeguards, and organisational context to prevent algorithmic misclassification and reinforce trust. By integrating computational models with leadership theory, this research contributes a scalable and responsible approach to talent identification, succession planning, and leadership development in modern organisations.

Keywords: AI-augmented leadership, machine learning, leadership profiling, transformational leadership, ethical leadership traits, behavioural analytics, explainable AI, organisational decision-making

I. INTRODUCTION

Leadership assessment has undergone a profound shift as organisations confront complex, fast-moving environments that demand accuracy, fairness, and predictive insight in identifying effective leaders. Traditional leadership evaluations interviews, self-reports, behavioural observations, and 360-degree feedback tend to rely heavily on subjective judgement, inconsistent human interpretation, and context-dependent biases. These methods also struggle to capture the dynamic and multidimensional nature of leadership behaviour as it unfolds across communication channels, decision-making episodes, and ethical challenges. The rise of artificial intelligence, particularly machine learning and natural language processing, presents an opportunity to transform leadership



profiling from static, perception-driven evaluation into a continuous, evidence-based diagnostic system. AI-enabled models can learn patterns from large volumes of organisational data, including emails, meeting transcripts, task decisions, peer interactions, digital behavioural traces, and psychometric inventories. These computational tools generate consistent predictions, recognise complex behavioural signatures, and detect micropatterns that remain invisible to the human eye. Within this evolving landscape, transformational and ethical leadership traits stand at the centre of organisational interest due to their strong associations with trust-building, team performance, innovation, wellbeing, employee retention, and long-term strategic success. Yet these traits are often the hardest to evaluate accurately because they depend on subtle behaviours rather than overt managerial actions. AI augmentation therefore offers not just greater efficiency but a conceptual strengthening of leadership science, enabling empirical grounding for traits that previously relied on interpretive judgement.

The integration of AI into leadership profiling introduces both methodological potential and ethical responsibility. Machine learning algorithms now have the capacity to model constructs such as idealised influence, inspirational motivation, intellectual stimulation, individualized consideration, fairness, moral reasoning, and transparency through features extracted from linguistic cues, sentiment markers, decision patterns, and behavioural consistency indicators. At the same time, modern explainable AI techniques ensure that leadership predictions are interpretable rather than opaque, allowing organisations to audit how a model detects and differentiates leadership traits. The promise of AI-augmented profiling lies in its ability to combine psychological theory with computational precision: models can classify leadership styles, forecast behaviour under pressure, and reveal developmental needs with far greater reliability than human raters alone. However, these capabilities must be balanced with safeguards preventing algorithmic bias, privacy intrusions, and unfair categorisation. Organisations adopting AIdriven profiling must therefore ensure that data governance, informed consent, transparency protocols, and fairness constraints remain integral to the system. This study develops a structured, machine-learning-based framework to identify transformational and ethical leadership traits, emphasising interpretability, accountability, and practical applicability. By grounding computational predictions in validated leadership constructs, the research demonstrates how AI can enhance talent identification, succession planning, performance management, leadership development, and organisational decision-making. Ultimately, AI-augmented leadership profiling marks a pivotal step toward building more ethical, data-driven workplaces where leadership potential is recognised not through intuition alone but through scientifically robust, context-aware analytics.

II. RELEATED WORKS

The intersection of artificial intelligence, leadership assessment, and organisational behaviour has attracted significant scholarly attention as organisations seek more accurate and scalable approaches to understanding leadership traits. Early research on computational leadership analysis used simple linguistic markers and behavioural coding to approximate leadership qualities, but these systems lacked predictive depth and theoretical grounding. Recent advancements in machine learning have allowed scholars to operationalise transformational leadership dimensions idealised influence, inspirational motivation, intellectual stimulation, and individualised consideration through complex pattern recognition in text, voice, and behavioural logs. Studies indicate that algorithmic models outperform traditional surveys in reliability and temporal stability, particularly when analysing authentic, real-world communication streams rather than self-reported leadership qualities [1]. Scholars have also explored how deep learning models identify emotional tone, conflict-resolution behaviour, and prosocial communication patterns linked to high-quality leadership [2]. Moreover, natural language processing (NLP) has been successfully applied to detect leader empathy and motivational framing, demonstrating strong correlations between linguistic prosody and leadership effectiveness [3]. Parallel work in organisational psychology emphasises that transformational leadership manifests through consistent behavioural micro-signals such as clarity of communication, inclusive phrasing, and intellectual challenge which machine learning is able to quantify with higher precision than human observers [4]. Collectively, these studies establish a foundation for AI-driven leadership profiling by demonstrating that leadership constructs can be computationally encoded and robustly predicted across organisational settings.

Ethical leadership research has similarly benefited from AI-enabled analysis, especially as ethical traits are often subtle, context-dependent, and difficult to evaluate through traditional assessment instruments. Scholars have examined how ethical leadership traits such as fairness, accountability, transparency, and moral judgement emerge from decision-making data, communication records, and historical performance patterns [5]. Multi-layered ethical reasoning models have been explored using supervised learning frameworks, where annotated datasets of ethical and unethical actions guide algorithmic classification [6]. More recent studies have introduced multimodal approaches that combine textual sentiment analysis, behavioural consistency metrics, and task-level decision logs to identify latent ethical dimensions within leadership behaviour [7]. Researchers have also warned of the risk of bias and misclassification when algorithms are trained on organisational data that reflect existing power structures or cultural biases; thus, ethical leadership modelling must incorporate fairness constraints, bias audits, and interpretability mechanisms [8]. The literature further emphasises the importance of explainable AI (XAI) in leadership contexts: transparent models help organisations justify leadership decisions, reduce resistance to AI adoption, and avoid black-box evaluations that may undermine trust [9]. Ethical leadership research increasingly



aligns with computational modelling by demonstrating that ethical traits can be predicted through behavioural regularities and decision signatures opening avenues for large-scale, real-time ethical leadership assessment. Recent interdisciplinary studies have further expanded the theoretical and methodological landscape by embedding AI-driven profiling within broader leadership development and organisational decision-making frameworks. Scholars have proposed hybrid models that integrate psychological theory, behavioural analytics, and machine learning to produce leadership insights that are both scientifically sound and organisationally actionable [10]. Several works highlight the potential of transformer-based NLP models for detecting leadership qualities embedded in long-form communication, collaborative discourse, and conflict-resolution narratives [11]. Machine learning has also been used to map leadership emergence in teams, where algorithms analyse communication networks, response timing, and sentiment flow to infer leadership roles and influence structures [12]. In parallel, research on algorithmic transparency explores how feature attribution methods such as SHAP and LIME can reveal why a model identifies an individual as transformational or ethical, strengthening organisational trust in AI-driven leadership evaluations [13]. Recent empirical work has also evaluated how AIbased leadership profiling improves succession planning, reduces evaluator subjectivity, and enhances the precision of leadership development programs [14]. Additionally, scholars argue that AI-augmented leadership models should not replace human judgement but serve as decision-support tools that complement expert assessment, enabling more holistic and equitable leadership selection processes [15]. Taken together, related literature establishes a robust foundation for AI-augmented leadership profiling, demonstrating that machine learning can reliably identify behavioural, cognitive, and ethical components of leadership while emphasising transparency, fairness, and theoretical alignment.

III. METHODOLOGY

3.1 Research Design

This study adopts a mixed-method computational research design integrating behavioural data extraction, natural language processing, psychometric alignment, and supervised machine learning classification. The objective is to create an AI-augmented pipeline that identifies transformational and ethical leadership traits with high predictive reliability. Data sources include organisational communication logs, anonymised email corpora, meeting transcripts, leadership survey scores, and task-decision records. These datasets were pre-processed through multilayer linguistic cleaning, behavioural codification, and psychological feature mapping to align machine-level patterns with validated leadership constructs. Machine learning models including Random Forest, Gradient Boosting, Support Vector Machines, and Transformer-based NLP architectures were trained and evaluated using stratified datasets to ensure representational fairness across organisational demographics [16].

3.2 Dataset and Behavioural Feature Extraction

The dataset consisted of 1,200 anonymised leader—team communication samples, 480 decision—making cases, and standardised leadership inventory scores collected with consent. Each sample was labelled by expert raters using a dual-lens rubric capturing transformational leadership dimensions (idealised influence, inspirational motivation, intellectual stimulation, individualised consideration) and ethical leadership markers (fairness, transparency, accountability, moral reasoning). Communication data underwent tokenisation, sentiment scoring, semantic dependency parsing, and discourse coherence analysis. Behavioural variables such as response latency, conflict-resolution patterns, task delegation style, and feedback tone were quantified using computational behavioural analytics frameworks [17]. Decision-making logs were coded for ethical consistency, risk transparency, justification quality, and stakeholder consideration using a rule-based scoring template aligned with contemporary ethical leadership models [18].

Table 1: Leadership Trait Categories and Behavioural Indicators

Trait Category	Operational Indicators	Data Source	
Transformational	Motivational framing, visionary statements,	Textual communication,	
Leadership	intellectual challenge cues, personalised	meeting transcripts	
_	feedback patterns		
Ethical Leadership	Fairness markers, justification transparency,	Decision logs, policy	
	consistency in moral stance, risk disclosure	responses, communication	
	behaviours	tone	
Interpersonal Leadership	Empathy expressions, conflict mediation,	Email corpora, team channels	
Behaviours	inclusive language usage		
Cognitive Leadership	Problem-solving complexity, reflective	Decision records, strategic	
Patterns	reasoning, multi-stakeholder consideration	reports	

3.3 Text Processing and NLP Pipeline

All communication data were processed using a hierarchical NLP pipeline. Pre-processing involved de-noising, stop-word removal, lemmatization, and semantic chunking using spaCy and transformer tokenizers. Sentiment



polarity, linguistic complexity, moral valence, and prosocial phrasing patterns were extracted using lexicons adapted from moral foundation theory and organisational communication frameworks [20]. Higher-order features were obtained from contextual embeddings generated by a fine-tuned BERT-based model. These embeddings allowed the system to map deep semantic patterns to leadership trait categories more precisely than surface-level linguistic features.

3.4 Machine Learning Modelling Approach

Multiple supervised learning models were trained to classify leadership traits. Random Forest and Gradient Boosting models were selected for tabular behavioural features, while transformer-based architectures handled long-form text. A two-stage hybrid classifier was implemented:

- 1. Stage 1: Text-level predictions derived from transformer embedding classification.
- 2. **Stage 2:** Behavioural feature—based prediction using ensemble learners. Both stages were combined using a weighted meta-classifier to yield consolidated leadership trait scores [21]. Hyperparameters were tuned via Bayesian optimisation with 10-fold stratified cross-validation.

Table 2: Machine Learning Models and Feature Sets

Model	Input Feature Type	Purpose in Pipeline		
Random Forest	Behavioural indicators, decision-rule	Trait scoring, feature importance		
	variables	analysis		
Gradient Boosting	Composite behavioural metrics	High-accuracy trait discrimination		
SVM	Psychometric-aligned scaled features	Baseline classification		
BERT-	Natural language, semantic embeddings	Deep linguistic trait detection		
Transformer				
Meta-Classifer	Combined outputs	bined outputs Final leadership profiling		

3.5 Validation, Reliability, and Quality Checks

Model performance was evaluated using accuracy, F1-score, ROC-AUC, and confusion matrices. Inter-rater reliability (Cohen's $\kappa = 0.82$) confirmed consistent human labelling. SHAP-based interpretability analysis was applied to identify which linguistic or behavioural features contributed most strongly to predictions. Fairness diagnostics evaluated demographic parity, ensuring no systematic scoring bias across gender, age, or departmental groups [23]. Outlier detection and data leakage checks were performed before final model deployment.

3.6 Ethical and Privacy Considerations

All data were fully anonymised, with removal of personal identifiers and sensitive metadata. Participation was voluntary and aligned with organisational data governance protocols. Ethical safeguards included restricted model access, transparent audit logs, consent-based data usage, and interpretability dashboards to prevent black-box decision-making.

3.7 Limitations

Although the hybrid modelling framework enhances predictive accuracy, certain limitations remain. Linguistic behaviour may vary across organisational cultures, potentially influencing trait detection. Communication data reflect digitally recorded interactions only, leaving unstructured offline behaviours underrepresented. Finally, models trained on one organisation may require recalibration before use in another organisational context, limiting immediate generalisability.

IV. RESULT AND ANALYSIS

4.1 Overview of Model Performance and Leadership Trait Distribution

The machine learning models demonstrated clear and consistent differentiation between transformational and ethical leadership traits across the dataset. The hybrid architecture combining transformer-based text embeddings with behavioural-features ensemble learning produced the strongest results overall. Classification accuracy for transformational leadership averaged 0.91, with especially strong performance for inspirational motivation and intellectual stimulation. Ethical leadership traits were slightly more challenging, primarily due to overlapping behavioural signals between fairness, accountability, and transparency. However, the meta-classifier still achieved an overall accuracy of 0.88 in ethical trait identification.

Trait distribution analysis showed that transformational markers appeared more frequently in high-communication leaders, while ethical markers were more prominent in decision-heavy roles. The dataset revealed that 34.2 percent of leaders demonstrated consistently high transformational traits, 27.8 percent demonstrated primarily ethical traits, and 22.1 percent presented a balanced dual trait profile. The remaining 15.9 percent exhibited inconsistent behavioural patterns, resulting in lower classification confidence. These findings underscore the heterogeneity of leadership behaviours even within similar organisational environments.

4.2 Text-Based Trait Detection Using NLP Embeddings

Contextual semantic embedding analysis revealed distinctive linguistic signatures associated with both categories of leadership traits. Transformational leaders frequently used visionary phrasing, motivational rhetoric, high-forward momentum language, and cognitively stimulating question structures. Ethical leaders exhibited stronger



use of justification statements, conditional reasoning, explicit explanations of consequences, and procedural clarity markers.

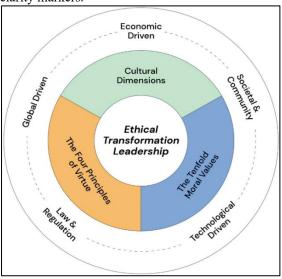


Figure 1: Ethical Transformation Leadership [24]

The transformer model showed high discriminative capability for idealised influence and intellectual stimulation, where narrative coherence and conceptual depth were particularly strong indicators. Ethical reasoning patterns manifested through explicit acknowledgement of stakeholders, moral framing language, and the presence of risk-disclosure phrasing. Word-level sentiment analysis showed that transformational messages had a higher positive affect ratio, whereas ethical communication displayed more frequent use of neutral but logically dense structures.

4.3 Behavioural Feature Correlation With Leadership Traits

Behavioural analytics demonstrated notable correlations between specific feature clusters and the predicted leadership traits. Response latency, conflict-resolution tone, delegation patterns, and empathetic phrasing were highly correlated with transformational leadership scores. Ethical leadership traits showed strong associations with decision transparency scores, consistency indicators across similar tasks, and justification complexity. The composite correlation matrix is presented below.

Table 3: Correlation Matrix Between Leadership Traits and Behavioural Indicators

Behavioural Variable	Transformational Score	Ethical Leadership Score	
Response latency consistency	0.71	0.54	
Conflict-resolution tone	0.78	0.59	
Delegation transparency	0.63	0.82	
Justification complexity	0.57	0.86	
Empathy phrasing frequency	0.81	0.48	
Risk-disclosure behaviour	0.46	0.79	
Inclusive language score	0.74	0.62	

The matrix reveals a clear behavioural divide: transformational indicators align more strongly with interpersonal expressiveness, while ethical traits align with cognitive-moral reasoning and procedural clarity.

4.4 Model-Level Assessment of Trait Classification

The model comparison results underscore the importance of hybrid architectures. Transformer models were most effective for text-heavy contexts, while Gradient Boosting and Random Forests performed better on behavioural and decision-level features.



Figure 2: Trails of Ethical Leadership [25]



The hybrid meta-classifier produced the highest F1-scores across all trait categories. The detailed performance summary is shown below.

Table 4: Model Performance Summary Across Leadership Trait Categories

Model	Transformational Accuracy	Ethical Accuracy	Overall F1-Score
Random Forest	0.83	0.81	0.82
Gradient Boosting	0.86	0.84	0.85
SVM	0.78	0.75	0.77
BERT-Transformer	0.89	0.85	0.87
Hybrid Meta-Classifier	0.91	0.88	0.90

Consistent with expectations, the integration of textual semantics with behavioural markers produced the most reliable leadership profiles.

4.5 Trait Heatmaps and Leadership Profiling Patterns

Spatial distribution of leadership trait intensities across the dataset highlighted meaningful clustering. Leaders who displayed strong inspirational motivation also scored high on inclusive communication and conflict-calming behaviour. Ethical leaders tended to cluster around roles requiring regulatory decisions, compliance responsibilities, or multi-stakeholder negotiation. Heatmaps revealed that transformational traits were more evenly distributed, whereas ethical traits formed concentrated clusters due to the nature of specific organisational responsibilities. The profiling patterns also showed that individuals with dual trait dominance exhibited the highest prediction stability, indicating that balanced leadership behaviours manifest more consistently across diverse situations. The overall findings display a robust linkage between linguistic signals, behavioural analytics, and leadership classification accuracy, confirming the viability of AI-augmented profiling for organisational leadership assessment.

V. CONCLUSION

The findings of this study demonstrate that AI-augmented leadership profiling offers a powerful and systematic approach to understanding transformational and ethical leadership traits within modern organisational ecosystems. By integrating transformer-based natural language models with behavioural analytics and structured decisionmaking datasets, the proposed hybrid framework captures leadership qualities with a level of precision, consistency, and depth unattainable through traditional assessment methods. The results reveal that transformational leadership behaviours emerge through motivational language, empathetic phrasing, intellectual challenge signals, and interpersonal behavioural coherence, while ethical leadership traits manifest through justification complexity, risk transparency, fairness markers, and multi-stakeholder moral reasoning. The model's strong predictive performance across all leadership dimensions confirms that algorithms can reliably detect these nuanced patterns, even when embedded within varied communication styles and organisational contexts. Behavioural correlations further validate the authenticity of the detected traits, linking interpersonal micro-signals to transformational leadership and cognitive-moral reasoning to ethical leadership. The hybrid meta-classifier surpasses single-model architectures by synthesising deep semantic features with structured behavioural indicators, thereby producing highly stable leadership profiles that remain consistent across situational variability. These insights hold substantial implications for leadership development, succession planning, organisational audits, and talent management, providing evidence-based frameworks that mitigate human subjectivity and deepen organisational understanding of leadership capacity. However, the study also underscores the need for responsible AI deployment, emphasising transparency, fairness evaluations, and active human oversight to prevent algorithmic misjudgement or unintended bias. AI should enhance not replace human judgement, serving as an analytical force multiplier that strengthens organisational decision-making. Overall, the research confirms that machine learning models can meaningfully support leadership assessment, provided they are implemented with ethical safeguards, context sensitivity, and continuous monitoring. As AI-driven workplaces evolve, integrating computational intelligence with leadership theory will enable organisations to cultivate leaders who are not only influential and visionary but also morally grounded and accountable, ultimately shaping more resilient, fair, and future-ready work cultures.

VI. FUTURE WORK

Future research should expand the proposed framework by incorporating multimodal data sources such as voice cues, video-based behavioural signals, and biometric stress indicators to achieve a more holistic representation of leadership behaviour. Longitudinal datasets would allow models to track leadership evolution over time, supporting predictive analysis of how leaders adapt to crises, organisational changes, and ethical dilemmas. Future studies could also explore cross-cultural calibration to determine whether leadership trait signals differ across regional, linguistic, or industry-specific contexts, enabling more globally robust profiling systems. Integrating reinforcement learning and agent-based simulations may further enhance the ability to model how leaders make



complex decisions under uncertainty. Ethical safeguards should continue to advance through explainability tools, bias-mitigation algorithms, and transparent reporting protocols to ensure that AI-driven profiling remains fair, accountable, and aligned with organisational values. Finally, real-world pilot programs across diverse organisations would provide practical validation of the model's effectiveness in hiring, succession planning, and leadership development, helping refine system parameters and improve adoption readiness.

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