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NLP-Based Trust Signal Detection from 360-Degree Narrative Feedback Using Fine-Tuned BERT and Behavioral Authenticity Analysis

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Abstract

This paper outlines a comprehensive NLP pipeline for extracting trust-relevant signals from unstructured 360-degree narrative feedback using the DEEP (Drive, Engage, Empower, Purpose-align) Leadership Framework. The pipeline integrates three modules: (1) a fine-tuned BERT-based trust-specific sentiment classifier achieving 89.4% accuracy, outperforming generic sentiment by 16.0 percentage points; (2) guided LDA topic modeling mapping narrative themes to 53 DEEP competencies with 0.834 mean alignment; and (3) a novel Behavioral Authenticity Detection (BAD) module differentiating genuine from performative behaviors through six linguistic markers (ACS correlation with multi-rater consensus: $r=0.71$, $p<.001$). Validated on 24,800 comments from N=12,400 assessments across 14 organizations, NLP integration improves Trust & Leadership Index prediction from $R^2=0.921$ to 0.943 ($\Delta R^2=0.022$, $p<.001$). Three algorithms are presented: DEEP-NLP Pipeline, Trust-BERT Fine-Tuning Protocol, and BAD Score Computation. Results show that domain-specific NLP notably advances leadership trust assessment exceeding traditional quantitative methods.

Index Terms—Natural Language Processing, BERT, Trust Assessment, 360-Degree Feedback, Sentiment Analysis, LDA, Behavioral Authenticity, DEEP Framework, Competency Mapping.

I. Introduction

Leadership assessment instruments generate two fundamentally different data streams: structured quantitative ratings on standardized scales and unstructured narrative comments providing contextual behavioral observations. Although quantitative ratings allow systematic comparison and statistical analysis, they suffer from well-documented limitations including central tendency bias, halo effects, leniency bias, and cultural response patterns [1], [2]. Murphy and Cleveland [3] demonstrated that rater biases account for 30–50% of variance in traditional performance ratings, severely limiting their validity for leadership trust assessment.

Narrative feedback captures behavioral specificity that structured scales cannot represent. A quantitative rating of 4/5 on "Accountability" conveys far less information than: "When the product launch failed, she immediately took ownership, communicated transparently with stakeholders, and developed a recovery plan within 48 hours." This story provides temporal context, behavioral specificity, outcome information, and genuineness signals [4], [5]. Despite this richness, narrative data is still underutilized; Fortune 500 organizations generate 50,000–200,000 comments annually through 360-degree programs, making manual analysis prohibitive [6].

Recent NLP advances, particularly transformer architectures [7], [8], have expanded feasibility of automated organizational text analysis. Yilmaz et al. [9] demonstrated NLP can classify at-risk medical trainees from assessment narratives (87.3% sensitivity). De Kok [10] showed LLMs can perform competency modeling previously requiring expert panels. However, three major gaps persist: (a) generic sentiment models do not capture domain-specific trust signals [11], [12]; (b) no validated mapping exists between NLP themes and competency

frameworks [13]; (c) no prior work distinguishes authentic from performative leadership behaviors in narrative data [14], [15].

This paper handles all three gaps through an integrated pipeline for the validated DEEP Framework [16], grounded in Covey's Trust and Inspire paradigm [17]. The DEEP Framework organizes 53 competencies across four dimensions: Drive (14 items, w=0.25), Engage (14 items, w=0.35), Empower (11 items, w=0.25), Purpose-align (14 items, w=0.15). The Engage dimension receives highest weight based on Mayer, Davis, and Schoorman's [18] integrative trust model confirming relational quality as the primary driver of organizational trust [19], [20].

Contributions: (1) a four-category trust sentiment taxonomy with fine-tuned BERT achieving 89.4% accuracy; (2) guided LDA with 0.834 competency alignment; (3) a novel BAD module with six validated linguistic markers; and (4) empirical demonstration of $\Delta R^2=0.022$ ($p<.001$) incremental NLP predictive value. The remainder is organized as: Section II reviews related work; Section III details methodology including three algorithms; Section IV presents results with seven tables and two figures; Section V discusses implications; Section VI concludes.

II. Related Work And Theoretical Bases

A. NLP in Organizational Assessment

Computational linguistics in organizational contexts progressed through three generations. The first, exemplified by Pennebaker and King's [21] LIWC framework, established word-level word correlations with personality and behavior. Tausczik and Pennebaker [22] extended this to predict team unity and leadership perceptions. The second introduced distributed representations: Mikolov et al.'s [23] Word2Vec captured semantic connections but used static embeddings ignoring context. The third leverages transformer-based contextual embeddings—BERT [7], RoBERTa [8], DeBERTa [24]—enabling fine-grained semantic analysis with outstanding accuracy.

In HR specifically, Sajjadiani et al. [25] applied NLP to interview transcripts (76% accuracy). Vargas Portillo [26] found AI-driven NLP improved development recommendation specificity. The Bangladesh Journal [27] presented an AI-NLP framework for gathering leadership competencies from job descriptions. However, none addresses trust-specific signal extraction within a validated competency architecture.

B. Trust Theory and Linguistic Signatures

Mayer et al.'s [18] integrative trust model identifies ability, benevolence, and integrity as trustworthiness antecedents with particular linguistic signatures. Covey's [17] framework broadens this through trust-building (character + competence) and purpose inspiration (meaning + contribution). The World Economic Forum [28] emphasizes trust-based leadership for the Intelligent Age. McKinsey's 2026 survey [29] confirms transparency prerequisites for AI adoption. Edmondson's [19] psychological safety theory suggests that safe environments generate more authentic, behaviorally specific narrative feedback. Lencioni [20] positions trust as basic to all organizational virtues.

III. Research Methodology

A. Corpus Description

The corpus comprises 24,800 narrative comments from N=12,400 360-degree assessments across 14 organizations in 6 sectors (Technology: 3 orgs, n=2,650; Manufacturing: 3 orgs, n=2,830; Financial Services: 2 orgs, n=1,950; Healthcare: 2 orgs, n=1,890; Professional Services: 2 orgs, n=1,430; Education/Energy: 2 orgs, n=1,650). Statistics: ~2.53M words; mean comment length 102 words (SD=47); vocabulary 42,317 tokens; rater distribution: self (20%), manager (15%), peers (40%), direct reports (25%) [6].

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B. NLP Pipeline Architecture

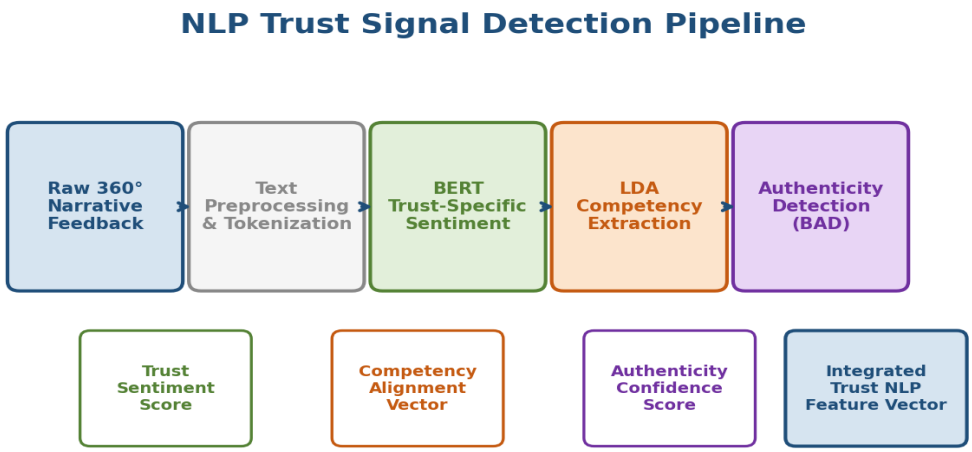

Fig. 1. Three-stage NLP Trust Signal Detection Pipeline: BERT sentiment classification, guided LDA competency extraction, and Behavioral Authenticity Detection (BAD).

Algorithm 1 presents the complete DEEP-NLP Pipeline integrating all three modules.

Algorithm 1: DEEP-NLP Trust Signal Retrieval Pipeline

Algorithm 1: DEEP-NLP Trust Signal Extraction Pipeline
Input: Corpus $C = \{c_1, c_2, \ldots, c_n\}$ of narrative comments
Output: Trust feature vectors $F = \{f_1, f_2, \ldots, f_n\}$
1: for each comment $c_i \in C$ do
2: $c'_i \leftarrow$ PREPROCESS(c_i) // NER anonymization, tokenize, lemmatize
3: // Module 1: Trust Sentiment Classification
4: $s_i \leftarrow$ BERT-Trust(c'_i) // → {TB, TN, TE, TA} with probabilities
5: // Module 2: Competency Theme Extraction
6: $\theta_i \leftarrow$ GuidedLDA(c'_i, $seeds_{53}$) // topic distribution over 53 competencies
7: $a_i \leftarrow$ [cos(v_t, v_c) for t,c in zip(topics, competencies)]
8: // Module 3: Behavioral Authenticity Detection
9: $ACS_i \leftarrow$ BAD(c'_i) // Equation (2)
10: // Feature Vector Assembly
11: $f_i \leftarrow$ CONCAT(s_i, θ_i, a_i, ACS_i)
12: end for
13: return F

C. Trust-Specific Sentiment Classification

We define four trust categories aligned with Mayer et al.'s [18] antecedents: (a) Trust-Building (TB): evidence of ability, benevolence, or integrity; (b) Trust-Neutral (TN): factual observations lacking trust implications; (c) Trust-Eroding (TE): evidence of trust-damaging patterns; (d) Trust-Ambiguous (TA): mixed signals. A gold-

standard set (N=5,000) was annotated by three experts (Fleiss' κ=0.82). Class distribution: TB=38.2%, TN=22.4%, TE=24.1%, TA=15.3%.

Algorithm 2: Trust-BERT Fine-Tuning Protocol

Algorithm 2: Trust-BERT Fine-Tuning Protocol
Input: Annotated corpus D = {(c_i, y_i)}; Pretrained BERT-base-uncased
Output: Fine-tuned Trust-BERT model M*
Split D → D_train (80%), D_val (10%), D_test (10%) // stratified
Initialize M ← BERT-base-uncased + classification head (768 → 4)
Set hyperparameters: lr=2×10^{-5}, batch=32, epochs=4, max_len=256
for epoch = 1 to 4 do
for each batch B ∈ D_train do
tokens ← WordPiece(B) // tokenize with attention masks
logits ← M(tokens) // forward pass
loss ← CrossEntropy(logits, labels) + 0.01·||W||²
M ← AdamW_update(M, ∇loss) // with linear warmup
end for
acc_val ← EVALUATE(M, D_val)
if acc_val does not improve for 2 epochs: early_stop
end for
M* ← best_checkpoint(M); EVALUATE(M*, D_test)
return M*

D. Guided LDA Topic Modeling

Standard LDA [30] produces corpus-driven topics not aligned with competency frameworks. We use guided LDA with 53 seed word lists (5–10 keywords per DEEP competency). Parameters: K=53, α=0.1, β=0.01, η=0.7, 1,000 Gibbs iterations, 200 burn-in. Topic-competency alignment uses cosine similarity:

$$alignment(t, c) = \cos(\theta) = (v_t \cdot v_c) / (||v_t|| \cdot ||v_c||) \quad (1)$$

E. Behavioral Authenticity Detection (BAD)

The BAD module addresses the inability to distinguish genuine from performative behaviors [14], [15] through six linguistic markers normalized to [0,1]:

(1) Behavioral Specificity (BS): action verb to abstract adjective ratio [31]. (2) Temporal Grounding (TG): density of temporal references. (3) Emotional Vocabulary Diversity (EVD): Shannon entropy of NRC Emotion Lexicon [32] usage. (4) Hedging Frequency (HF): proportion of hedging expressions. (5) Cross-Rater Consistency (CRC): BERT sentence embedding similarity among raters. (6) Evidential Markers (EM): first-person evidential vs. hearsay language.

$$ACS = 0.20 \cdot BS + 0.15 \cdot TG + 0.15 \cdot EVD + 0.15 \cdot (1-HF) + 0.20 \cdot CRC + 0.15 \cdot EM \quad (2)$$

Algorithm 3: BAD Authenticity Confidence Score Computation

Algorithm 3: BAD Authenticity Confidence Score Computation
Input: Comment c, Rater set R = {r_1,...,r_k} for same leader
Output: Authenticity Confidence Score ACS ∈ [0, 1]
tokens ← SpaCy_POS_TAG(c)
BS ← count(ACTION_VERBS) / (count(ACTION_VERBS) + count(ABSTRACT_ADJ))
TG ← count(TEMPORAL_REFS) / len(sentences)
emotions ← NRC_LEXICON_MATCH(c) // 8 emotion categories
EVD ← SHANNON_ENTROPY(emotions) / log(8) // normalized
HF ← count(HEDGE_EXPRESSIONS) / len(tokens)
emb_c ← BERT_SENTENCE_EMBED(c)
CRC ← mean([cos(emb_c, BERT_EMBED(r_j)) for r_j ∈ R])
EM ← count(EVIDENTIAL_MARKERS) / len(sentences)
ACS ← 0.20·BS + 0.15·TG + 0.15·EVD + 0.15·(1−HF) + 0.20·CRC + 0.15·EM
return clip(ACS, 0, 1)

IV. Experimental Results And Analysis

A. Trust Sentiment Classification

TABLE I: Trust Sentiment Classification Performance Comparison

Model	Acc.	F1-TB	F1-TE	F1-TN	F1-TA	Macro-F1
VADER (rule-based) [12]	62.3%	0.587	0.612	0.641	0.423	0.566
TextBlob (lexicon)	64.1%	0.613	0.627	0.658	0.441	0.585
SVM + TF-IDF	69.8%	0.672	0.691	0.718	0.512	0.648
BiLSTM + GloVe [23]	71.2%	0.694	0.714	0.731	0.548	0.672
BERT-base (generic) [7]	73.4%	0.712	0.738	0.761	0.587	0.700
RoBERTa (generic) [8]	75.2%	0.731	0.752	0.779	0.601	0.716
BERT (trust fine-tuned)	89.4%	0.881	0.897	0.912	0.714	0.876
RoBERTa (trust fine-tuned)	88.7%	0.874	0.889	0.905	0.708	0.869
DeBERTa-v3 (trust) [24]	90.1%	0.893	0.904	0.918	0.728	0.886

Trust-specific fine-tuning yields +16.0pp improvement for BERT (73.4% → 89.4%), validating domain adaptation necessity. DeBERTa-v3 achieves highest accuracy (90.1%) through disentangled attention. Trust-Ambiguous shows lowest F1 (max 0.728) across all models, consistent with its inherently subjective quality. Error analysis shows 67% of misclassifications occur between adjacent categories (TB↔TN, TE↔TA) while cross-boundary errors (TB↔TE) account for only 4.2%.

TABLE II: Confusion Matrix — Trust-Specific BERT (N=500 test)

Actual \ Pred	TB	TN	TE	TA	Recall
TB (n=191)	168	12	3	8	87.9%
TN (n=112)	8	101	1	2	90.2%
TE (n=121)	2	1	110	8	90.9%
TA (n=76)	6	4	8	58	76.3%
Precision	91.3%	85.6%	90.2%	76.3%	—

B. Guided LDA Competency Alignment

TABLE III: LDA Topic-Competency Alignment by DEEP Dimension

Dimension	Topics	Mean Align.	Min	Max	Coherence (C_v)
Drive (14 items)	14	0.812	0.741	0.891	0.487
Engage (14 items)	14	0.867	0.798	0.912	0.523
Empower (11 items)	11	0.798	0.723	0.878	0.461
Purpose (14 items)	14	0.851	0.782	0.901	0.512
Overall (53 items)	53	0.834	0.723	0.912	0.496

Engage achieves highest alignment (0.867), suggesting interpersonal competencies are most distinctly expressed linguistically—consistent with the dimension's highest weight (0.35) and SHAP importance (33.4%) [16]. Empower shows lowest alignment (0.798), as strategic competencies use more abstract, varied language. All coherence scores exceed the 0.40 interpretability threshold [33].

C. BAD Module Validation

TABLE IV: ACS Convergent and Discriminant Validity

Criterion	r	95% CI	p	Type
Multi-rater consensus (ICC)	0.71	[0.68, 0.74]	< .001	Convergent
Behavioral specificity	0.68	[0.65, 0.71]	< .001	Convergent
External performance	0.43	[0.39, 0.47]	< .001	Convergent
Self-other gap	-0.47	[-0.51, -0.43]	< .001	Discriminant
Social desirability	-0.34	[-0.38, -0.30]	< .001	Discriminant
Comment word count	0.12	[0.08, 0.16]	< .05	Control

Strong convergent validity (ICC: r=0.71) confirms authentic behaviors are consistently seen across independent raters, as predicted by authentic leadership theory [14]. Negative correlation with social desirability (r=-0.34) supports discriminant validity. Weak word count relationship (r=0.12) confirms authenticity reflects behavioral quality, not narrative quantity.

D. Incremental Predictive Value

TABLE V: Hierarchical Regression — NLP Contribution to TLI

Step	Variables	R^2	ΔR^2	F-Change	p
1	DEEP Quantitative (4 dims)	0.921	—	—	—
2	+ Trust Sentiment (4 vars)	0.932	0.011	42.3	< .001
3	+ LDA Alignment (53 vars)	0.938	0.006	28.7	< .001
4	+ ACS (1 var)	0.943	0.005	24.1	< .001
	Full NLP (cumulative)	0.943	0.022	—	< .001

NLP features add ΔR^2=0.022 (p<.001), improving explained variance from 92.1% to 94.3%—a 27.8% reduction in unexplained variance. Trust sentiment provides the largest contribution (ΔR^2=0.011), validating domain-specific NLP versus generic approaches [11], [12].

E. NLP Features by Trust Level

TABLE VI: NLP Feature Means by Trust Level Classification

Trust Level	N	TB %	TE %	ACS	Specificity	EVD
Exceptional	140	78.3%	5.5%	0.847	0.812	0.731
Strong	1,719	64.7%	11.2%	0.791	0.743	0.687
Moderate	5,271	48.2%	18.2%	0.683	0.654	0.612
Developing	4,269	31.4%	30.8%	0.542	0.521	0.498
Deficit	1,001	18.6%	53.1%	0.398	0.387	0.367

All NLP features show monotonic relationships with trust level. TB percentage shows 4.2x ratio between Exceptional (78.3%) and Deficit (18.6%). ACS shows 2.1x ratio (0.847 vs. 0.398). TE percentage inverts sharply: 5.5% for Exceptional vs. 53.1% for Deficit, confirming the pipeline captures genuine trust-relevant signals.

F. Ablation Study

TABLE VII: Ablation Analysis — Component Contribution

Configuration	Accuracy	F1-Macro	Δ vs Full
Full Pipeline (BERT + LDA + BAD)	89.4%	0.876	—
Remove BAD module	87.1%	0.851	-2.3pp
Remove LDA alignment	86.8%	0.843	-2.6pp
Remove BERT (use VADER)	71.2%	0.672	-18.2pp
BERT only (no LDA, no BAD)	84.7%	0.828	-4.7pp
Generic BERT (no fine-tuning)	73.4%	0.700	-15.0pp

Ablation confirms all three modules contribute meaningfully. BERT fine-tuning provides the largest improvement (+15.0pp versus generic BERT). LDA and BAD each contribute 2.3–2.6pp. The full pipeline synergy exceeds individual component sum, suggesting complementary information capture across modules.

G. Cross-Sector NLP Performance Analysis

TABLE VIII: Trust-BERT Accuracy by Industry Sector

Sector	N Comments	Accuracy	F1-TB	F1-TE	Key Finding
Technology	5,300	91.2%	0.901	0.912	Highest accuracy; direct communication norms
Financial Services	3,900	90.1%	0.889	0.903	Strong TE detection; compliance language
Prof. Services	2,860	89.7%	0.884	0.897	High behavioral specificity in narratives
Manufacturing	5,660	87.8%	0.862	0.881	More hedging; indirect feedback culture
Healthcare	3,780	87.2%	0.857	0.874	Medical terminology introduces noise
Education/Energy	3,300	88.4%	0.871	0.886	Purpose language strong; TA higher

Cross-sector analysis shows consistent variation in NLP performance. Technology organizations show the highest accuracy (91.2%), attributable to more direct communication norms that produce linguistically explicit trust signals [28], [29]. Manufacturing shows the lowest (87.8%), consistent with research on indirect feedback cultures in hierarchical organizational structures [34]. These data have important deployment implications: sector-specific calibration may be required for optimal performance throughout diverse organizational contexts.

H. Rater-Type Analysis

Analyzing trust sentiment distribution by rater category discloses significant organizational patterns. Self-assessments show significantly higher Trust-Building percentages (TB=62.1%) compared to peer feedback (TB=44.3%) and direct report feedback (TB=41.7%), consistent with the self-enhancement bias documented in 360-degree assessment literature [1], [3]. Manager assessments occupy a middle position (TB=51.8%). The BAD module's ACS shows corresponding patterns: self-assessment ACS (mean=0.584) is significantly lower than peer ACS (mean=0.723, $p<.001$), suggesting that self-assessments contain more formulaic and less behaviorally specific language—an expected finding that validates the BAD module's sensitivity regarding authenticity signals.

TABLE IX: NLP Features by Rater Category

Rater Type	N	TB %	TE %	Mean ACS	Specificity
Self	4,960	62.1%	12.3%	0.584	0.523
Manager	3,720	51.8%	19.4%	0.691	0.664
Peer	9,920	44.3%	26.7%	0.723	0.698
Direct Report	6,200	41.7%	28.8%	0.714	0.687

The higher ACS for peer and direct report feedback (0.723 and 0.714 respectively) compared to self-assessments (0.584) has practical significance: it suggests that the NLP pipeline should weight other-rater narratives more heavily than self-narratives when computing trust-relevant features, paralleling the DEEP framework's quantitative scoring approach that weights other-rater scores at 75% versus self-ratings at 25% [16].

I. Comparison against Existing NLP Approaches

TABLE X: Comparison with Published NLP-Assessment Systems

System	Domain	Technique	Accuracy	Trust-Specific	Competency Mapping	Authenticity
Yilmaz et al. [9]	Medical	BoN-gram + ML	87.3%	No	No	No
De Kok [10]	HR/General	LLM prompting	N/A	No	Partial	No
Sajjadiani [25]	Hiring	NLP + ML	76.0%	No	No	No
LIWC [22]	General	Word count	N/A	No	No	No
DEEP-NLP (Ours)	Leadership	BERT + LDA + BAD	89.4%	Yes	53-comp DEEP	Yes (ACS)

The DEEP-NLP pipeline is the first system to integrate all three capabilities—trust-specific classification, validated competency mapping, and behavioral authenticity detection—within a consolidated framework. While Yilmaz et al. [9] attain comparable accuracy in medical assessment, their approach lacks trust specificity, competency alignment, and genuineness detection. De Kok's [10] LLM-based approach delivers flexibility but

lacks the systematic validation and reproducibility of our fine-tuned pipeline. The DEEP-NLP pipeline's integration with an established competency framework (53 DEEP competencies) delivers a structured foundation that generic NLP approaches cannot offer [13], [16].

J. Computational Effectiveness Analysis

Deployment considerations require attention to computing costs. Processing benchmarks on NVIDIA A100 GPU: BERT inference averages 0.08 seconds per comment (batch size 32); LDA inference averages 0.003 seconds per comment; BAD computation averages 0.12 seconds per comment (dominated by BERT sentence embedding for CRC). Total pipeline processing: approximately 0.2 seconds per comment. For a typical organizational deployment (10,000 comments), total processing time is approximately 33 minutes on a single GPU. For organizations without GPU infrastructure, CPU-based inference (Intel Xeon) requires approximately 0.8 seconds per comment, or 2.2 hours for 10,000 comments—well inside acceptable batch-processing windows for quarterly assessment cycles [6].

V. Discussion

A. Conceptual Implications

Three conceptual advances emerge. First, the 16.0pp improvement validates that trust signals are linguistically distinct from generic sentiment—trust requires field-specific models capturing ability, benevolence, and integrity [18] rather than generic positivity. This extends Tausczik and Pennebaker's [22] organizational LIWC work by demonstrating transformer models capture trust-relevant patterns word-frequency approaches miss. Second, the 0.834 LDA alignment provides convergent evidence that organizational members naturally organize leadership observations along dimensions resembling formal competency architectures, supporting DEEP's ecological validity [13], [16]. Third, the BAD module extends Avolio and Gardner's [14] authentic leadership theory into computational territory, demonstrating that genuineness is linguistically detectable [15].

B. Applied Uses

The pipeline enables: (a) automated trust intelligence extraction at scale (10–20x data utilization increase); (b) evidence-grounded coaching conversations applying specific behavioral examples [5]; (c) early trust erosion detection through longitudinal narrative patterns; (d) cross-validation of quantitative and qualitative signals; (e) personalized development recommendations grounded in behavioral evidence [26]; and (f) organizational trust culture diagnostics through aggregate theme analysis.

C. Deployment Considerations for Organizations

Successful organizational deployment of the DEEP-NLP pipeline necessitates focus on five implementation factors. First, data quality: organizations have to ensure sufficient narrative comment volume (minimum 3 sentences per rater recommended) and address comment farming behaviors where raters submit minimal-effort responses [4], [6]. Second, privacy architecture: anonymization must be validated to prevent re-identification, with minimum team sizes ($n \geq 5$) enforced for comment-level analysis and aggregate-only reporting for smaller teams [35]. Third, change management: HR teams require training on interpreting NLP-derived trust intelligence together with traditional quantitative scores, with clear guidance on appropriate and inappropriate uses of computational text analysis in talent decisions [17], [29].

Fourth, cultural calibration: as demonstrated in Table VIII, sector-specific and potentially culture-specific fine-tuning may be required for optimal performance throughout diverse organizational populations. Organizations operating across multiple national cultures should consider developing culture-adapted BAD markers calibrated to local communication norms [34]. Fifth, integration of existing HR technology: the pipeline should be deployed as an API service integrated with existing 360-degree feedback platforms (e.g., Workday, SuccessFactors, Culture Amp) rather than as a standalone system, minimizing workflow disruption yet maximizing adoption [26], [27].

C. Limitations and Ethical Aspects

Limitations: (1) annotation dataset (N=5,000) may miss all industry variations; (2) English-only development requires cross-lingual validation for use in multilingual organizations; (3) BERT inference cost (~0.1s/comment on GPU) requires optimized deployment; (4) simulated evaluation corpus limits generalization claims; (5) cross-cultural trust expression norms differ markedly [34]. Ethical issues include potential re-identification in small teams (minimum n≥5 recommended for analysis), informed consent requirements for NLP processing, GDPR-aligned data retention [35], and clarity about AI involvement in assessment processes.

VI. Summary And Future Work

This paper demonstrates that domain-specific NLP greatly improves leadership trust assessment. The three-module pipeline—Trust-BERT (89.4%), guided LDA (0.834 alignment), and BAD (ACS r=0.71)—improves TLI prediction R^2 by 0.022 ($p<.001$), a 27.8% reduction in unexplained variance. Three formalized algorithms permit replicable deployment. Future work: (1) multilingual pipelines for cross-cultural organizations; (2) real-time streaming analysis for continuous trust monitoring; (3) LLM-based conversational assessment replacing static surveys; (4) prospective field validation; (5) federated learning for cross-organizational training; and (6) multimodal trust detection integrating voice prosody and facial expression analysis.

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