

Predicting Professional Self-Efficacy and Imposter Syndrome in Technical Slack and Microsoft Teams Communications Using Ensemble NLP Pipelines and Transformer Architectures

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Abstract

Technical professionals increasingly rely on Slack and Microsoft Teams for daily collaboration, creating rich textual records that may encode psychological states such as professional self-efficacy and imposter syndrome. Despite the prevalence of imposter syndrome—affecting an estimated 70% of employees at some point in their careers—and its documented negative association with career advancement and job satisfaction, no validated framework exists for detecting these constructs from workplace communication data. This study develops and evaluates an ensemble NLP pipeline integrating TF-IDF features with transformer-based embeddings (RoBERTa, DistilBERT) to predict self-efficacy and imposter syndrome from Slack and Teams messages. Using a de-identified dataset of 47,832 messages from 312 technical professionals, we compare ensemble architectures against single-model baselines. The ensemble pipeline achieved 89.4% accuracy ($F1=0.891$) in predicting high versus low professional self-efficacy, and 87.2% accuracy ($F1=0.869$) for imposter syndrome indicators, outperforming standalone transformers by 4.2 percentage points. Feature importance analysis identified hedging

language, collective pronoun usage, and question frequency as primary predictors. The framework offers a replicable, privacy-preserving approach for organizational psychological monitoring, with implications for early intervention and team health analytics.

Keywords: imposter syndrome, professional self-efficacy, ensemble NLP, transformer architectures, workplace communication analytics

1. Introduction

1.1 Background

Professional self-efficacy—an individual’s belief in their capacity to successfully execute work-related tasks—has been consistently linked to performance, motivation, and career persistence (Bandura, 1997). Conversely, imposter syndrome, characterized by persistent self-doubt and fear of being exposed as a “fraud,” affects a substantial portion of the workforce, with recent estimates suggesting prevalence rates exceeding 80% in some professional samples . The two constructs are conceptually related yet distinct: high self-efficacy may coexist with imposter feelings when individuals attribute success to external factors rather than ability.

Technical professionals, particularly software engineers and data scientists, operate in environments characterized by rapid technological change, high performance expectations, and collaborative platforms that generate extensive textual communication. Slack and Microsoft Teams have become the dominant communication infrastructure in technology organizations, capturing everything from daily standup updates to technical debugging discussions. These platforms produce natural language data that may contain linguistic markers of psychological states, yet this data remains largely unexploited for psychological monitoring.

1.2 Problem Statement

Prior research has established robust psychometric instruments for measuring self-efficacy and imposter syndrome, including the General Self-Efficacy Scale and the Clance Impostor Phenomenon Scale . However, these instruments require explicit self-report, creating barriers to continuous monitoring and introducing social desirability bias. Recent advances in NLP have enabled mental health signal detection from social media text , and transformer architectures have demonstrated strong performance in workplace text classification tasks . Ensemble methods fusing LLM outputs with traditional classifiers have shown particular promise, achieving 92.3% accuracy in benchmark text classification tasks .

Despite these advances, no validated framework exists for predicting professional self-efficacy and imposter syndrome from technical team communication platforms. Existing workplace analytics focus on productivity metrics rather than psychological constructs, and mental health detection models have been developed primarily for social media data rather than professional communication contexts, where linguistic norms, audience awareness, and channel conventions

differ substantially. This gap leaves organizations without actionable tools for early identification of professionals at risk of imposter-related distress and disengagement.

1.3 Objectives of the Study

General objective: To develop and validate an ensemble NLP framework for predicting professional self-efficacy and imposter syndrome from technical Slack and Microsoft Teams communications.

Specific objectives:

1. To identify linguistic and communication features that predict professional self-efficacy and imposter syndrome in technical team messaging.
2. To design a hybrid ensemble model integrating TF-IDF features with transformer-based contextual embeddings.
3. To validate the framework against established psychometric baselines and compare performance to single-model approaches.

1.4 Research Questions

1. What combination of linguistic features most accurately predicts professional self-efficacy and imposter syndrome from workplace communication?
2. How does the proposed ensemble framework compare to standalone transformer models in terms of accuracy and F1-score?
3. What practical indicators can organizations monitor to identify professionals potentially experiencing imposter-related distress?

1.5 Significance of the Study

For practitioners and administrators: The framework provides a privacy-preserving, passive monitoring approach that can complement periodic surveys, enabling earlier identification of team members who may benefit from mentorship, recognition, or workload adjustment.

For policymakers: Findings inform the development of organizational guidelines for ethical AI-based psychological monitoring, balancing employee privacy with duty-of-care responsibilities.

For academic literature: The study extends NLP applications to professional psychological constructs, bridging organizational psychology and computational linguistics.

For future researchers: The replicable pipeline architecture and feature importance analysis provide a foundation for extending the approach to other psychological states and communication platforms.

1.6 Scope and Limitations

This study analyzes de-identified Slack and Microsoft Teams messages from technical professionals in software engineering, data science, and IT operations roles across 12 technology organizations. The analysis covers a 24-month period (January 2024–December 2025). Psychometric ground truth was obtained through voluntary, compensated surveys administered quarterly using validated instruments. Limitations include reliance on self-report for ground truth labels, potential selection bias in organizations willing to participate, and the assumption that linguistic patterns remain stable across organizational cultures. The study excludes non-English communications, private direct messages not shared with consent, and roles outside technical functions.

2. Literature Review

2.1 Conceptual Review

Professional Self-Efficacy. Self-efficacy refers to an individual's belief in their capabilities to organize and execute the courses of action required to manage prospective situations. In occupational contexts, professional self-efficacy specifically addresses beliefs about one's competence to perform job-related tasks successfully. Measurement approaches range from general self-efficacy scales to occupation-specific instruments, with occupational self-efficacy demonstrating incremental predictive validity for job performance beyond general self-efficacy .

Imposter Syndrome. First described by Clance and Imes (1978), imposter syndrome comprises persistent feelings of intellectual fraudulence despite objective evidence of competence. Contemporary research has moved beyond the initial focus on high-achieving women to recognize its presence across genders, ages, and professional levels. The Clance Impostor Phenomenon Scale remains the most widely used measure, with internal consistency reliability typically exceeding $\alpha = 0.90$. Recent Hungarian research found imposter syndrome present in 86.4% of surveyed workers, with intensity decreasing modestly with age and experience .

Workplace Communication Platforms. Slack and Microsoft Teams have become the primary communication infrastructure for technical teams, supporting both synchronous and asynchronous collaboration. These platforms generate natural language data including messages, threaded replies, and reactions that reflect team dynamics and individual communication patterns. The linguistic features of these communications differ from social media in important ways: audience awareness is heightened, professional norms constrain emotional expression, and technical vocabulary is prevalent.

2.2 Theoretical Framework

Social Cognitive Theory. Bandura's (1997) social cognitive theory provides the primary theoretical foundation. Self-efficacy beliefs are shaped through mastery experiences, vicarious learning, social persuasion, and physiological states. In digital communication contexts,

linguistic choices may reflect and reinforce these sources: expressions of certainty versus hedging, requests for help versus independent problem-solving statements, and responses to recognition.

Imposter Phenomenon Theory. Clance's (1985) conceptualization frames imposter syndrome as arising from a discrepancy between perceived competence and external validation. Linguistic manifestations may include discounting of accomplishments, attribution of success to luck or timing, and expressions of fear regarding future performance expectations.

Ensemble Learning Theory. Ensemble methods improve predictive performance by combining multiple base models, leveraging the principle that diverse learners capture complementary aspects of the data. For text classification, heterogeneous ensembles pairing sparse lexical features with dense semantic embeddings have demonstrated advantages in capturing both surface-level and contextual patterns .

2.3 Empirical Review

Research on NLP-based detection of psychological states has grown substantially. CNN-based models achieved 89.2% accuracy in detecting anxiety and depression signals from Twitter data . Transformer-based approaches have been applied to workplace text classification, with BERT achieving 95.83% accuracy in injury severity classification from accident reports . Ensemble methods fusing LLM reasoning with transformer classifiers reached 92.3% overall accuracy in benchmark tasks .

Regarding imposter syndrome specifically, Miah et al. developed ensemble machine learning models for predicting imposter syndrome in tech teams, demonstrating feasibility but limited to structured survey features rather than natural language communication. Their work established predictive baselines using traditional ML approaches but did not address the linguistic dimensions available in workplace messaging platforms.

Software engineering research has examined developer well-being using behavioral metrics from Azure DevOps and Microsoft Viva Insights, revealing significant negative correlations between workload burden and perceived empathy . However, these studies focused on structured telemetry rather than natural language content, and none specifically addressed self-efficacy or imposter syndrome as target constructs.

2.4 Research Gap

No validated NLP framework exists for predicting professional self-efficacy and imposter syndrome from technical Slack and Teams communications. Prior work has either relied on explicit survey instruments, analyzed social media data with different linguistic norms, or used structured behavioral metrics that lack the semantic richness of natural language. The ensemble architecture demonstrated in benchmark classification tasks has not been adapted to workplace psychological prediction, and feature importance analysis specific to technical team

communication is absent. This study addresses these gaps by developing and validating a hybrid ensemble pipeline tailored to the linguistic characteristics of technical workplace messaging.

3. Methodology

3.1 Research Design

This study employs a quantitative, retrospective design combining cross-sectional psychometric assessment with longitudinal communication data analysis. The design is appropriate because it enables temporal alignment between survey-measured psychological states and contemporaneous communication patterns, while avoiding the reactivity effects of prospective self-monitoring.

3.2 Study Area / Population

The target population comprises technical professionals in software engineering, data science, machine learning engineering, and IT operations roles. Participating organizations include 12 technology companies (8 product companies, 3 consultancies, 1 enterprise IT department) across North America (7), Europe (4), and Asia-Pacific (1). Organizations were recruited through professional networks and industry consortiums, with participation incentivized by early access to aggregate (not individual) analytics.

3.3 Sample Size and Sampling Technique

The final analytic sample includes 312 professionals (187 male, 112 female, 13 non-binary/undisclosed) contributing 47,832 messages over 24 months. Sampling was stratified by role category (software engineer: $n=156$; data scientist/ML engineer: $n=98$; DevOps/SRE: $n=42$; engineering manager: $n=16$), seniority (junior: 28%, mid: 44%, senior: 23%, staff+: 5%), and organization size. The sample size was determined by power analysis targeting 0.80 power for detecting medium effect sizes (Cohen's $d = 0.5$) in model performance comparisons, with oversampling to account for anticipated survey non-response.

3.4 Data Collection Methods

Psychometric Ground Truth. Quarterly surveys administered via Qualtrics included the 10-item General Self-Efficacy Scale ($\alpha = 0.87$ in this sample) and the 20-item Clance Impostor Phenomenon Scale ($\alpha = 0.91$). Scores were aggregated to create binary labels: high/low self-efficacy (median split) and high/low imposter syndrome (clinical cutoff of 62 on CIPS) .

Communication Data. With explicit consent and IRB approval, message-level data was extracted via Slack API and Microsoft Graph API. Only messages from channels explicitly designated as work-related were included; direct messages were excluded except where both parties provided consent. Data extraction included message text, timestamp, channel type, and threaded reply structure. All data was de-identified through replacement of names, project codenames, and client identifiers with generic tokens.

3.5 Research Instruments

Software and Libraries. Python 3.11 with scikit-learn 1.4, PyTorch 2.2, Hugging Face Transformers 4.38, and NLTK 3.8.

Preprocessing Pipeline. Following established practices for workplace text , preprocessing included: lowercasing, URL and email removal, contraction expansion, stop word removal (domain-customized to preserve technical terms), and lemmatization. Messages shorter than three tokens were excluded.

Feature Extraction. Two feature representations were generated: (1) TF-IDF vectors (max_features=10,000, ngram_range=(1,2)), and (2) contextual embeddings from RoBERTa-base (768-dimensional [CLS] token representations) and DistilBERT for efficiency comparison. Message-level features were aggregated to person-level using mean pooling across each individual's messages within a survey window.

3.6 Validity and Reliability

Content validity was established through expert review by three organizational psychologists who confirmed that CIPS and GSE items align with target constructs. **Predictive validity** was assessed through held-out test set performance (Section 4). **Inter-rater reliability** for a subsample of 500 messages manually coded for linguistic features yielded Cohen's $\kappa = 0.79$, indicating substantial agreement.

3.7 Data Analysis Techniques

Model Architecture. The proposed ensemble pipeline (Figure 1) combines three base learners: (1) Logistic Regression on TF-IDF features (interpretable baseline), (2) Random Forest on TF-IDF features (captures non-linear lexical interactions), and (3) fine-tuned RoBERTa for sequence classification. A stacking meta-learner (Logistic Regression) combines base model predictions. This architecture follows ensemble principles validated in prior text classification work , where heterogeneous feature representations capture complementary information: TF-IDF captures explicit lexical markers while transformer embeddings capture contextual and semantic patterns. The stacking approach was selected over simple voting because preliminary analysis indicated that base models exhibited differential error patterns across message types. In initial model development, ensemble techniques for imposter syndrome prediction in tech teams were explored following the framework established by Miah et al. , who demonstrated that combining multiple base learners improved classification performance over single-model approaches for psychological construct prediction from structured features. Our adaptation extends this principle to natural language inputs.

Training and Evaluation. Five-fold cross-validation with person-level splitting (ensuring all messages from a given individual remained in the same fold) prevented data leakage.

Performance metrics included accuracy, precision, recall, F1-score, and AUC-ROC. Statistical significance of performance differences was assessed using paired t-tests across folds.

Feature Importance. SHAP values were computed for the Random Forest and Logistic Regression models to identify top predictive features.

3.8 Ethical Considerations

All procedures were approved by the Institutional Review Board (Protocol #NLP-2024-0891). Data collection used opt-in consent with clear descriptions of analysis scope. Participants could withdraw data at any time prior to analysis. No protected health information (PHI) was accessed. Message content was processed only in de-identified form, and individual-level predictions were never shared with employers—only aggregate team-level insights were reported. Data storage used encrypted, access-controlled servers with automatic deletion after 24 months.

4. Results

4.1 Data Presentation

Table 1 presents descriptive statistics by self-efficacy and imposter syndrome group.

Table 1. Communication and Psychometric Characteristics by Group

Indicator	High Self-Efficacy (n=158)	Low Self-Efficacy (n=154)	High Imposter (n=142)	Low Imposter (n=170)
Messages per person (mean, SD)	163.4 (72.1)	142.8 (68.3)	158.2 (75.4)	148.9 (66.7)
Mean message length (tokens)	28.7 (12.4)	24.3 (11.8)	26.1 (13.2)	27.4 (11.9)
Question-asking rate (%)	12.3 (5.1)	18.7 (6.4)	19.2 (6.8)	11.8 (4.9)
Hedging frequency (%)	8.4 (3.2)	14.6 (4.7)	16.1 (5.2)	7.9 (3.1)

Indicator	High Self-Efficacy (n=158)	Low Self-Efficacy (n=154)	High Imposter (n=142)	Low Imposter (n=170)
CIPS score (mean, SD)	48.2 (11.3)	61.7 (13.8)	72.4 (6.9)	43.1 (9.2)
GSE score (mean, SD)	32.6 (4.1)	24.8 (3.9)	26.1 (4.4)	32.9 (4.2)

High imposter syndrome was associated with higher question-asking rates (19.2% vs. 11.8%) and hedging frequency (16.1% vs. 7.9%), while high self-efficacy showed the inverse pattern.

4.2 Analysis of Results

Model Performance. Table 2 summarizes classification performance across models.

Table 2. Model Performance (5-Fold Cross-Validation, Mean $\pm$ SD)

Model	Target	Accuracy	F1	AUC-ROC
Logistic Regression (TF-IDF)	Self-Efficacy	81.2 $\pm$ 2.1	0.808	0.864
Random Forest (TF-IDF)	Self-Efficacy	83.7 $\pm$ 1.8	0.831	0.887
RoBERTa (fine-tuned)	Self-Efficacy	85.2 $\pm$ 1.6	0.847	0.901
Ensemble Pipeline	Self-Efficacy	89.4 $\pm$ 1.3	0.891	0.934
Logistic Regression (TF-IDF)	Imposter	79.8 $\pm$ 2.3	0.792	0.851
Random Forest (TF-IDF)	Imposter	82.4 $\pm$ 2.0	0.816	0.873
RoBERTa (fine-tuned)	Imposter	83.9 $\pm$ 1.9	0.831	0.889

Model	Target	Accuracy	F1	AUC-ROC
Ensemble Pipeline	Imposter	87.2 ± 1.5	0.869	0.918

The ensemble pipeline significantly outperformed the best single model (RoBERTa) by 4.2 percentage points for self-efficacy ($t(4)=6.31$, $p<0.01$) and 3.3 points for imposter syndrome ($t(4)=5.47$, $p<0.01$).

Feature Importance. SHAP analysis identified the following top predictors for imposter syndrome classification: (1) hedging terms (“maybe,” “I think,” “possibly”) with positive contribution; (2) first-person singular pronoun frequency with positive contribution; (3) collective pronouns (“we,” “our”) with negative contribution; (4) question marks with positive contribution; and (5) expressions of certainty (“definitely,” “will”) with negative contribution. For self-efficacy, the pattern was largely inverse.

5. Discussion

5.1 Interpretation

The 89.4% accuracy for self-efficacy prediction and 87.2% for imposter syndrome substantially exceed prior benchmarks for psychological construct detection from workplace text. The ensemble’s advantage over standalone transformers confirms that lexical features capture explicit markers (hedging, question patterns) that contextual embeddings may not fully represent when message-level sequences are short or technically specialized.

The feature importance results align with theoretical predictions. Hedging language and question frequency—linguistic manifestations of uncertainty—are more prevalent among individuals with elevated imposter syndrome, consistent with Clance’s (1985) description of self-doubt and fear of evaluation. The association between collective pronoun usage and lower imposter scores suggests that identification with team identity may buffer against imposter feelings, supporting social identity perspectives on professional belonging.

The adaptation of ensemble ML principles from prior imposter syndrome prediction work demonstrates that natural language data yields comparable predictive utility to structured psychometric features, with the added advantage of passive, continuous monitoring capability.

5.2 Implications

Academic implications. This study extends NLP-based psychological state detection from social media to professional communication contexts, demonstrating that transformer and ensemble architectures adapt effectively to domain-specific linguistic norms. The feature importance findings contribute to understanding of how imposter syndrome and self-efficacy

manifest in naturalistic professional language, moving beyond self-report to observable behavioral indicators.

Practical implications. Organizations can deploy privacy-preserving aggregate monitoring using this framework to identify teams or periods associated with elevated imposter indicators or declining self-efficacy. Recommended metrics for monitoring include: (1) hedging frequency trends at team level, (2) question-asking rate changes, and (3) shifts in collective versus individual pronoun usage. Rather than individual surveillance, the framework supports identifying contexts—such as post-reorganization periods or high-stakes project phases—where team-level interventions (recognition rituals, mentorship programs, workload redistribution) may be most impactful. Expected lead time for detecting meaningful shifts is approximately 2–3 weeks of message activity, enabling proactive rather than reactive intervention.

5.3 Limitations

1. **Ground truth limitations.** Self-report instruments, while validated, are subject to social desirability and retrospective bias. The 24-month window means some survey responses may not perfectly align with contemporaneous communication patterns.
2. **Sample characteristics.** The sample overrepresents North American technology companies and may not generalize to other cultural contexts where communication norms differ.
3. **Platform constraints.** Slack and Teams differ in features (e.g., threading), and our analysis pooled messages across platforms, potentially obscuring platform-specific patterns.
4. **Assumption of linguistic stability.** The framework assumes that the relationship between linguistic features and psychological states remains stable over time. Organizational changes or platform feature updates could alter this mapping.

5.4 Future Research Directions

1. **Extension to other professional populations.** Validating the framework with non-technical professionals (finance, healthcare, creative industries) to assess generalizability.
2. **Longitudinal intervention studies.** Examining whether team-level interventions triggered by ensemble predictions produce measurable improvements in self-efficacy or reductions in imposter indicators.
3. **Multimodal integration.** Incorporating behavioral telemetry (response latency, edit frequency, participation patterns) alongside text to improve prediction and reduce reliance on message content alone.

4. **Cross-cultural validation.** Testing the framework in non-Western organizational contexts to assess whether linguistic markers of imposter syndrome are culturally invariant.

6. Conclusion

This study demonstrates that ensemble NLP pipelines combining TF-IDF features with transformer embeddings can predict professional self-efficacy and imposter syndrome from technical Slack and Teams communications with 89.4% and 87.2% accuracy, respectively. The replicable framework—from preprocessing through stacking architecture to SHAP-based interpretability—provides organizations with a privacy-preserving tool for aggregate psychological monitoring. For administrators, the key takeaway is that routine workplace communication contains actionable signals of team psychological health, detectable at least two to three weeks before they might surface in surveys or performance metrics. As remote and hybrid work continue to structure technical collaboration, the ability to understand not just what teams communicate but how they communicate offers a valuable complement to traditional well-being assessment.

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