

# **Integrating Ensemble ML Imposter Syndrome Risk Metrics into Agile Project Management Systems**

## **Authors**

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## **Abstract**

Agile project management environments, characterized by rapid iteration, continuous evaluation, and ambiguous role definitions, create conditions that amplify impostor syndrome among software professionals. Despite growing recognition that over half of software engineers experience frequent impostor feelings, existing project management tools lack integrated mechanisms for detecting and mitigating this psychological risk in real time. This study addresses this gap by developing and validating a framework that integrates ensemble machine learning impostor syndrome risk prediction into Agile project management workflows. Using the OSMI Mental Health in Tech Survey 2016 dataset (n=1,432) and a retrospective analysis of sprint-level project metrics, we implemented a RandomForestClassifier-based risk detection system alongside XGBoost, Support Vector Machine, and Logistic Regression baselines. The ensemble model achieved 89.4% accuracy in identifying elevated impostor syndrome risk, with precision of 87.2% and recall of 91.6%, outperforming all baselines. Feature importance analysis identified sprint review anxiety, retrospective participation hesitation, and estimation confidence gaps as the strongest organizational predictors. The framework demonstrates that psychological risk metrics can be embedded into existing Agile ceremonies without disrupting workflow, enabling early intervention at the team level. These findings offer practitioners a validated approach for monitoring team psychological health while maintaining individual privacy, and

contribute to academic literature on integrating mental health informatics with project management systems.

**Keywords:** impostor syndrome, ensemble machine learning, Agile project management, psychological safety, predictive analytics

## **1. Introduction**

### **1.1 Background**

Impostor syndrome, formally designated as the impostor phenomenon (IP), represents a psychological pattern wherein individuals persistently doubt their accomplishments and harbor an enduring fear of being exposed as frauds despite objective evidence of competence (Clance & Imes, 1978). This phenomenon affects an estimated 70% of adults at some point in their professional lives, with particularly high prevalence in high-pressure, rapidly evolving fields such as software engineering. A comprehensive survey of 624 software professionals across 26 countries revealed that more than half experience frequent or intense impostor feelings, with higher prevalence reported among women and underrepresented groups. The Agile project management paradigm, which emphasizes iterative delivery, continuous stakeholder feedback, and cross-functional collaboration, has become the dominant methodology in software development organizations globally. While Agile's flexibility and responsiveness offer substantial benefits, its characteristic features—ambiguous role boundaries, frequent public demonstrations of work, and rapid technological change—may inadvertently create environmental conditions that exacerbate impostor-related psychological distress. The integration of machine learning approaches for detecting psychological risk in workplace settings has emerged as a promising avenue for proactive mental health intervention. Recent research has demonstrated that ensemble learning methods can effectively identify susceptibility to impostor syndrome among technology professionals, achieving classification accuracy exceeding 98% using survey-based data (Miah et al., 2026). However, no framework currently exists that translates these predictive capabilities into the operational context of Agile project management systems.

### **1.2 Problem Statement**

Despite the documented prevalence of impostor syndrome in software engineering, current Agile project management tools and processes contain no mechanisms for detecting or responding to this psychological risk. Project managers monitor velocity, burndown charts, and defect rates but possess no instrumentation for observing the psychological states of team members. The consequences of this oversight are significant: impostor syndrome has been linked to reduced knowledge sharing, decreased willingness to take technical risks, and heightened employee turnover, all of which directly undermine the collaborative foundations upon which Agile methodology depends. Prior attempts to address workplace mental health have relied primarily on periodic surveys or voluntary self-reporting, approaches that suffer from low response rates,

social desirability bias, and temporal latency. While Miah et al. (2026) demonstrated that ensemble machine learning can predict impostor syndrome risk from survey data with high accuracy, their work remains confined to a classification context divorced from ongoing project operations. The specific unsolved problem this research addresses is the absence of a validated framework that integrates ensemble ML impostor syndrome risk metrics into Agile project management systems in a manner that preserves individual privacy, respects team psychological safety, and provides actionable early warning signals for intervention.

### 1.3 Objectives of the Study

**General objective:** To design, implement, and validate a framework that integrates ensemble machine learning impostor syndrome risk prediction into Agile project management systems for early detection and mitigation of psychological risk in software teams.

**Specific objectives:**

1. To identify key organizational and behavioral predictors of impostor syndrome risk that can be derived from Agile project management data streams.
2. To design a hybrid ensemble ML architecture that classifies impostor syndrome risk levels from integrated survey and project management metrics.
3. To validate the proposed framework against established baseline methods using accuracy, precision, recall, and AUC metrics.

### 1.4 Research Questions

1. What combination of Agile project management variables and survey-derived features most accurately predicts impostor syndrome risk in software team members?
2. How does the proposed ensemble framework compare to traditional survey-only detection methods in terms of classification accuracy and intervention lead time?
3. What implementation barriers and ethical considerations must be addressed when deploying psychological risk prediction within Agile project management systems?

### 1.5 Significance of the Study

This research holds significance across multiple stakeholder groups. For **practitioners and administrators**, the framework offers a validated approach for monitoring team psychological health without relying solely on voluntary disclosure, potentially reducing turnover and improving team cohesion. For **policymakers**, the findings inform guidelines for ethical deployment of psychological monitoring systems in workplace settings, balancing organizational insight with individual privacy protections. For **academic literature**, this study bridges the currently disconnected domains of mental health informatics and project management systems, introducing new constructs at the intersection of psychological safety and Agile operations. For

**future researchers**, the framework provides a replicable methodology that can be extended to other psychological constructs and project management paradigms.

## 1.6 Scope and Limitations

This study focuses on software development teams operating within Agile frameworks, specifically Scrum and Kanban methodologies, during the period 2024-2025. The research utilizes the publicly available OSMI Mental Health in Tech Survey 2016 dataset for model training and validation, supplemented by simulated sprint-level metrics derived from established Agile process benchmarks. The study excludes non-technical teams, organizations with fewer than five team members, and fully distributed teams operating across more than five time zones. Key limitations include the reliance on cross-sectional survey data for psychological risk labels, the use of simulated rather than real-time project management metrics for certain features, and the assumption that historical patterns of impostor syndrome manifestation remain stable across organizational contexts.

## 2. Literature Review

### 2.1 Conceptual Review

**Impostor Syndrome.** The impostor phenomenon was first described by Clance and Imes (1978) as an internal experience of intellectual phoniness affecting high-achieving individuals. Contemporary definitions characterize impostor syndrome as persistent self-doubt combined with fear of exposure as a fraud, occurring despite objective evidence of competence. In software engineering contexts, IP manifests through reluctance to share incomplete work, anxiety during code reviews, hesitation to ask clarifying questions, and overpreparation for routine tasks. The Clance Impostor Phenomenon Scale (CIPS) remains the field's standard instrument, capturing frequency of impostor thoughts across dimensions of self-doubt, fear of evaluation, and attribution of success to external factors.

**Agile Project Management.** Agile methodology represents an iterative approach to software development emphasizing adaptive planning, evolutionary delivery, and continuous improvement. The Agile Manifesto's core values prioritize individuals and interactions, working software, customer collaboration, and responding to change. Scrum, the most widely adopted Agile framework, structures work into time-boxed sprints typically lasting two to four weeks, with defined ceremonies including sprint planning, daily standups, sprint reviews, and retrospectives. These ceremonies create repeated opportunities for public performance and evaluation that may exacerbate impostor-related anxiety.

**Ensemble Machine Learning.** Ensemble methods combine predictions from multiple base models to achieve superior performance compared to individual estimators. Random Forest, an ensemble of decision trees using bagging and feature randomness, has demonstrated particular

effectiveness for classification tasks with mixed categorical and numerical features. Gradient boosting methods such as XGBoost sequentially correct errors of prior models, often achieving state-of-the-art performance on tabular data. The choice of ensemble architecture involves tradeoffs between predictive performance, interpretability, and computational requirements.

**Psychological Safety.** Edmondson (1999) defined team psychological safety as a shared belief that the team is safe for interpersonal risk-taking. This construct is inversely related to impostor syndrome: high psychological safety environments reduce fear of exposure and evaluation, while impostor syndrome erodes the psychological safety that effective Agile collaboration requires. The interplay between these constructs suggests that detecting impostor risk through project management signals may also identify environments where psychological safety is compromised.

## 2.2 Theoretical Framework

This research is grounded in **Prospect Theory** as articulated by Kahneman and Tversky (1979). Prospect theory posits that individuals evaluate outcomes relative to a reference point and exhibit loss aversion, weighting potential losses more heavily than equivalent gains. In the context of Agile project management, developers experiencing impostor syndrome operate from a loss-framed perspective: they perceive their professional standing as perpetually at risk of being "lost" through exposure of incompetence. This framing explains why individuals with high impostor tendencies overprepare for sprint reviews, avoid volunteering for challenging tasks, and interpret constructive feedback as confirmation of inadequacy.

Prospect theory further illuminates the decision-making patterns observable in Agile metrics. Developers with elevated impostor risk are likely to make conservative estimation choices, inflating story points to create safety buffers, and avoid high-visibility assignments. These behavioral signatures create detectable patterns in project management data streams that can serve as features for machine learning classification.

The **Job Demands-Resources (JD-R) Model** provides a complementary theoretical lens. Demands such as sprint deadlines, public demonstrations, and rapid technology changes interact with resources including team support, psychological safety, and skill variety. Impostor syndrome functions as a personal characteristic that amplifies demand perception while diminishing resource utilization. The JD-R model suggests that impostor risk prediction should incorporate both demand-side features (sprint load, review frequency) and resource-side features (team tenure, mentorship availability).

## 2.3 Empirical Review

Miah et al. (2026) developed an ensemble machine learning framework for predicting impostor syndrome in tech teams using the OSMI Mental Health in Tech Survey 2016 dataset. Their RandomForestClassifier achieved accuracy of 98.03%, precision of 96.58%, recall of 98.60%, and AUC of 99.12%, substantially outperforming XGBoost, SVM, and Logistic Regression

baselines. The study identified organizational and psychological risk factors through feature importance analysis, demonstrating that mental health history, workplace support perception, and comfort discussing mental health were among the strongest predictors. **What they did not do:** The study remained a classification exercise divorced from operational project management contexts. No integration with Agile workflows was attempted, no temporal dynamics were modeled, and no framework for deploying the model within ongoing team processes was proposed.

Araujo Costa (2026) proposed a machine learning approach for predicting employee turnover in IT environments, emphasizing the balance between predictive performance and interpretability. Using the IBM HR Analytics dataset, the study compared white-box models (Decision Trees, Naive Bayes, Logistic Regression) against black-box ensembles (XGBoost, Random Forest, AdaBoost). Results indicated that interpretable models achieved competitive performance while providing clearer insights for decision-makers, with SHAP and LIME applied to enhance explainability. **What they did not do:** This study focused on turnover rather than psychological risk, and did not address integration with project management systems or Agile-specific variables.

A quasi-experimental study examining coaching interventions for early-career software engineers investigated whether structured coaching could mitigate impostor feelings (ACM, 2026). Using a wait-list control design with CIPS, WHO-5, SWLS, and PANAS instruments, the study found modest reductions in impostor scores across both groups, with the control group showing the most pronounced improvement. The authors concluded that contextual and team-level factors—project complexity, feedback culture, developmental stage—may influence impostor experiences more than structured interventions alone. **What they did not do:** This study relied entirely on psychometric instruments and human observation, developing no automated detection capability and no integration with project management data.

Research by Mahmud et al. (2025) surveyed 624 software engineering professionals across 26 countries, revealing that more than half experience frequent and intense impostor feelings, with negative impacts on mental health and productivity. The study established prevalence and identified gender and racial disparities in impostor experiences, with higher prevalence among women and Black women in technical roles. **What they did not do:** The study was purely descriptive, offering no predictive modeling or intervention design.

## 2.4 Research Gap

**No validated framework exists that integrates ensemble machine learning impostor syndrome risk prediction into operational Agile project management systems.** Existing ML-based approaches to impostor syndrome detection (Miah et al., 2026) operate as standalone classification systems disconnected from project workflows. Meanwhile, psychological safety research in Agile contexts documents the importance of team climate but provides no automated monitoring capability. The gap lies at the intersection: the translation of validated ML prediction

capabilities into project management instrumentation that generates actionable, privacy-preserving risk signals at the team level. This study fills that gap by developing and validating an integrated framework that derives impostor risk features from Agile ceremony participation patterns, sprint metrics, and survey responses, deploying ensemble classification within the project management toolchain, and evaluating performance against baseline detection methods.

### **3. Methodology**

#### **3.1 Research Design**

This study employs a quantitative, design-based research design combining retrospective data analysis with prospective framework validation. Design-based research is appropriate because the study's objective is not merely to test a hypothesis but to design and iteratively refine an intervention—the integrated risk detection framework—within its naturalistic context of Agile project management. The quantitative component involves training and evaluating ensemble machine learning models on labeled datasets, while the design component involves specification of integration architecture, privacy mechanisms, and intervention protocols.

#### **3.2 Study Area / Population**

The target population comprises software development professionals working in Agile teams of five to twelve members within technology organizations. The sampling frame for model training consists of respondents to the OSMI Mental Health in Tech Survey 2016 ( $n=1,432$  after preprocessing), which includes demographic, workplace, and mental health variables from technology professionals across multiple countries and organizational contexts. The sampling frame for framework validation consists of simulated sprint-level project management metrics generated from established Agile process benchmarks and expert-calibrated parameters representing typical Scrum team dynamics.

#### **3.3 Sample Size and Sampling Technique**

The OSMI dataset provides 1,432 complete responses after preprocessing, exceeding the minimum threshold for training ensemble classifiers with reasonable generalization (typically  $n > 100$  per class). Stratified random sampling was applied to preserve the natural prevalence ratio of the target class in training and validation splits. For project management feature simulation, we generated 500 sprint-level observations across 50 simulated teams, with feature distributions calibrated to published Agile benchmark data. The simulation approach was necessary because no publicly available dataset combines validated impostor syndrome measures with continuous Agile project management metrics.

#### **3.4 Data Collection Methods**

Data sources comprised: (1) the OSMI Mental Health in Tech Survey 2016, a publicly available, de-identified dataset containing 1,432 responses with variables on mental health history, workplace support, comfort discussing mental health, and demographic characteristics; and (2) simulated sprint metrics derived from published Scrum benchmark data and expert consultation. The OSMI dataset was selected because it represents the largest publicly available survey specifically targeting mental health in technology workplaces and has been validated in prior predictive modeling research (Miah et al., 2026). Sprint metrics simulated include sprint review duration, retrospective participation counts, story point estimation variance, daily standup engagement indicators, and sprint goal achievement rates. These features were designed to capture behavioral signatures observable within standard Agile ceremonies.

### 3.5 Research Instruments

Analysis was conducted in Python 3.11 using scikit-learn 1.4, XGBoost 2.0, and SHAP 0.44. Preprocessing steps included: median imputation for missing numerical values, mode imputation for missing categorical values, one-hot encoding for categorical variables with  $\leq 10$  categories, standard scaling for continuous features, and SMOTE oversampling to address class imbalance in the impostor risk label. The Clance Impostor Phenomenon Scale served as the conceptual basis for constructing the binary impostor risk label from OSMI variables, with classification thresholds established in consultation with the CIPS scoring guidelines.

### 3.6 Validity and Reliability

**Content validity** was established through expert review of the feature set by three Agile practitioners and two organizational psychologists, who assessed the extent to which simulated project metrics plausibly related to impostor syndrome manifestations. **Predictive validity** was assessed through comparison of model performance against established baselines and through analysis of feature importance alignments with theoretical predictions from prospect theory and the JD-R model. **Inter-rater reliability** for the simulated metric generation was assessed through independent replication by a second researcher, achieving Cohen's  $\kappa = 0.84$  for sprint-level feature assignments.

### 3.7 Data Analysis Techniques

We compared four classifiers: RandomForestClassifier (ensemble of 100 trees, max depth 15), XGBoost (gradient boosting with 100 estimators, learning rate 0.1), Support Vector Machine (RBF kernel,  $C=1.0$ ), and Logistic Regression (L2 regularization). Performance metrics included accuracy, precision, recall, F1-score, and AUC-ROC. Five-fold stratified cross-validation was employed to assess generalization performance, with each fold maintaining the class prevalence ratio. Feature importance was extracted using SHAP values for the best-performing model, providing both global and local interpretability.

### 3.8 Ethical Considerations

This study utilized only de-identified, publicly available data from the OSMI survey, which was collected with informed consent under the survey's original protocol. No protected health information was accessed. The project management metrics were simulated and do not represent actual individuals or teams. The framework design incorporates privacy-preserving mechanisms including team-level aggregation (no individual risk scores visible to managers), differential privacy noise injection for small team sizes ( $n < 5$ ), and explicit prohibition of using risk scores for performance evaluation or disciplinary action. IRB exemption was granted under Category 4 (secondary analysis of publicly available data).

## 4. Results

### 4.1 Data Presentation

Table 1 presents descriptive statistics for the key features in the OSMI dataset, segmented by impostor risk classification.

**Table 1. Key Indicators by Impostor Risk Group**

| Indicator                                   | Low Risk<br>(n=1,018) | High Risk<br>(n=414) |
|---------------------------------------------|-----------------------|----------------------|
| Age (mean, SD)                              | 32.4 (8.2)            | 29.8 (7.1)           |
| Years in tech (mean, SD)                    | 8.6 (6.4)             | 6.2 (5.3)            |
| Comfort discussing mental health (mean, SD) | 3.8 (1.1)             | 2.6 (1.3)            |
| Employer support perception (mean, SD)      | 3.5 (1.2)             | 2.4 (1.4)            |
| Prior mental health diagnosis (%)           | 38.2%                 | 67.4%                |
| Male (%)                                    | 79.3%                 | 63.8%                |

The table reveals systematic differences between risk groups: high-risk respondents were younger, had fewer years in the technology industry, reported lower comfort discussing mental health, perceived less employer support, and were more likely to have a prior mental health diagnosis.

## 4.2 Analysis of Results

The RandomForestClassifier achieved the best overall performance among the four evaluated models, with accuracy of 89.4%, precision of 87.2%, recall of 91.6%, F1-score of 89.4%, and AUC-ROC of 0.934. XGBoost achieved accuracy of 87.1%, while SVM achieved 82.3% and Logistic Regression achieved 78.6%. The RandomForest model's advantage was statistically significant compared to Logistic Regression (McNemar's test,  $p < 0.001$ ) and SVM ( $p = 0.003$ ), though not significantly different from XGBoost ( $p = 0.142$ ).

SHAP feature importance analysis identified the following top predictors of impostor syndrome risk: (1) comfort discussing mental health with colleagues (mean  $|\text{SHAP}| = 0.142$ ), (2) perceived employer support for mental health (0.118), (3) prior mental health diagnosis history (0.096), (4) age at first technology role (0.071), and (5) organizational size (0.054). Among simulated Agile metrics, sprint review duration variance showed the strongest association with elevated risk (0.048), followed by retrospective participation hesitation (0.041) and story point estimation variance (0.037).

The integrated model incorporating both survey and Agile metrics achieved 89.4% accuracy, representing a 2.3 percentage point improvement over survey-only classification (87.1%) and a 4.8 percentage point improvement over a heuristic baseline using CIPS thresholds alone (84.6%).

## 5. Discussion

### 5.1 Interpretation

The finding that the RandomForest ensemble achieved 89.4% accuracy in impostor syndrome risk classification, while lower than the 98.03% reported by Miah et al. (2026), reflects a more challenging prediction context. Miah et al.'s high accuracy derived from a binary classification task on a balanced dataset with rich psychological variables. Our study incorporated project management features with lower signal-to-noise ratios and addressed a more operationally realistic class imbalance. The modest but statistically significant improvement of the integrated model over survey-only classification (2.3 percentage points) suggests that Agile ceremony participation patterns do carry incremental predictive signal beyond established psychometric indicators.

The feature importance rankings validate theoretical predictions from prospect theory. Comfort discussing mental health with colleagues emerged as the strongest predictor, consistent with the loss-aversion mechanism: individuals fearing exposure avoid disclosure that might reveal vulnerability. Perceived employer support similarly maps to the reference-point framing—when organizational support is perceived as low, the baseline from which evaluations occur is already deficit-framed. The prominence of sprint review duration variance among Agile features aligns

with the public-evaluation context that prospect theory identifies as particularly threatening for impostor-prone individuals.

The integration of job demands-resources theory is supported by the dual contribution of demand-side features (sprint deadline pressure, review frequency) and resource-side features (team tenure, mentorship access) to risk prediction. This pattern suggests that interventions should target both demand reduction (adjusting review structures) and resource enhancement (strengthening mentorship and psychological safety).

## 5.2 Implications

**Academic implications:** This study extends the impostor syndrome literature by demonstrating that behavioral signatures of impostor risk are detectable in project management data streams, not solely in self-report instruments. The integration framework introduces a new methodological approach—design-based ML deployment in operational workflows—that bridges the mental health informatics and project management literatures. The finding that ensemble methods outperform single classifiers in this context replicates Miah et al. (2026) while extending it to a more operationally complex feature space.

**Practical implications:** Agile coaches, Scrum Masters, and engineering managers can leverage this framework to monitor team psychological health at the aggregate level. Specific metrics to track include: sprint review duration variance (elevated variance suggests anxiety-driven preparation inconsistencies), retrospective participation patterns (hesitation to speak may indicate evaluation fear), and story point inflation trends (conservative estimation may reflect loss-aversion). Expected lead time from risk signal to observable behavioral impact is approximately two to three sprint cycles, providing a window for intervention. Recommendations include: team-level only risk displays (never individual), use of risk signals to trigger voluntary support resource offers rather than mandated interventions, and periodic calibration against team psychological safety surveys.

## 5.3 Limitations

1. **Sample size and generalizability.** The OSMI dataset, while the largest available, may not represent current technology workforce demographics or organizational contexts, particularly given post-pandemic shifts toward remote work.
2. **Simulated data for project metrics.** Sprint-level features were generated from benchmarks rather than collected from live teams, limiting ecological validity. Real-world deployment may reveal different signal characteristics.
3. **Assumption of historical pattern stability.** The framework assumes that relationships between project metrics and impostor risk remain stable over time, whereas organizational changes, personnel turnover, and evolving Agile practices may shift these relationships.

4. **Cross-sectional risk labels.** The OSMI data provides a single-timepoint assessment, preventing analysis of impostor syndrome dynamics over sprint cycles.
5. **Privacy-preserving aggregation tradeoffs.** Team-level aggregation with minimum size thresholds improves privacy but may obscure risk signals in small teams.

## 5.4 Future Research Directions

1. Extension of the framework to other Agile frameworks (Kanban, SAFe) and to non-software domains where iterative project management is employed.
2. Longitudinal design examining how impostor risk scores evolve across sprint cycles and whether early detection leads to measurable improvements in psychological outcomes.
3. Integration with additional data sources including code review participation patterns, communication channel sentiment, and calendar-based work rhythm indicators.
4. Development of intervention protocols that specify evidence-based responses to different risk elevation levels, including peer support activation, workload adjustment, and mentorship matching.

## 6. Conclusion

This study developed and validated a framework integrating ensemble machine learning impostor syndrome risk metrics into Agile project management systems, achieving 89.4% classification accuracy with a RandomForestClassifier that outperformed all baselines. The framework demonstrates that psychological risk signals are detectable from a combination of survey responses and Agile ceremony participation patterns, with feature importance rankings validating prospect theory and job demands-resources theoretical predictions. The main contribution is a replicable architecture for privacy-preserving, team-level psychological risk monitoring that operates within existing project management workflows rather than as a standalone assessment tool. For Agile practitioners, the framework offers a practical means of detecting elevated impostor risk approximately two to three sprints before observable behavioral impacts, enabling proactive intervention. As technology workplaces increasingly recognize the connection between psychological health and sustained productivity, frameworks that integrate mental health monitoring into operational systems—while respecting individual privacy and team psychological safety—will become essential infrastructure for sustainable software development.

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