Combining Passive Sensing and Self-Reported Symptoms with Network Analysis to Predict Suicidal Ideation in Medical Residents

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Abstract

Medical residents experience high levels of occupational stress, which elevates their vulnerability to mental health challenges, including suicidal ideation. This study aims to develop a predictive framework for identifying suicide risk in this population by constructing networks from passive sensing data (e.g., step count, sleep metrics) and self-reported mental health assessments (e.g., daily mood ratings, PHQ-9, GAD-7). Using data from the Intern Health Study conducted in 2018–2019, we will employ graph-based machine learning to capture complex, temporal relationships among these behavioral and psychological variables. Key network-derived topological features, such as degree centrality and clustering coefficients, will be extracted and used to train machine learning classifiers. Comparative evaluations of traditional classifiers and advanced graph neural network (GNN) architectures will be conducted to assess both predictive accuracy and interpretability. By using graph-based ML to *preserve the networked nature of mental health and behavioral data*, this project aims to develop a predictive tool for detecting suicide risk among medical residents, supporting targeted intervention strategies in high-stress professional environments.

1 Introduction

1.1 Background and Motivation

Suicidal ideation is a critical global health issue and among the top 20 leading cause of death (7), particularly in high-stress populations such as medical residents (1). These individuals face unique occupational challenges, including long hours, sleep deprivation, and high-stakes decision-making, which can exacerbate mental health issues such as depression, anxiety, and burnout (mental health in medical residents). Traditional mental health assessment methods often rely on static, self-reported measures collected at discrete intervals, which may miss dynamic changes in mental health and behavior that precede suicidal ideation. Advances in wearable technology and passive sensing provide an opportunity to continuously monitor behavioral patterns, such as sleep and physical activity, offering rich, real-time insights into mental health (6). However, integrating such multimodal data into meaningful and interpretable frameworks for suicide risk prediction remains a challenge.

Recent research has explored network-based approaches to mental health, constructing networks where nodes represent symptoms or behaviors and edges capture their relationships (8; 3). These methods have been increasingly applied in domains such as depression, anxiety, and autism, to uncover how symptoms interact, as measured by brain connectivity, self-report, and behavioral data (9; 2; 5; 4), demonstrated that network metrics, such as centrality and shortest path, can reveal critical

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symptoms that drive mental health conditions . Additionally, graph machine learning methods have shown promise in leveraging these relational structures for predictive tasks (8).

Building on this foundation, this study aims to construct symptom-behavior networks using passive sensing and self-reported data from the Intern Health Study, a longitudinal cohort of medical residents. *The primary objective is to identify medical residents at risk for suicidal ideation* by integrating passive sensing data (e.g., step count, sleep metrics) with self-reported mental health assessments (e.g., daily mood ratings, PHQ-9, GAD-7, C-SSRS) collected during the 2018–2019 cohorts. Suicidal ideation refers to thoughts about or preoccupation with self-harm or suicide, as measured by validated mental health instruments. In this study, it is captured using the **Columbia-Suicide Severity Rating Scale (C-SSRS)** during quarterly self-report assessments. By combining network analysis with traditional machine learning techniques, the study seeks to improve the prediction of suicidal ideation and uncover actionable insights into the complex relationships between mental health symptoms and behavioral patterns. We will use the Predictability, Computability, and Stability (PCS) framework, throughout our data cleaning, preprocessing, analysis, and results presentation.

Our research is guided by a shared interest on improving *population mental health*. Alexander Quispe, with a background in economics, brings expertise in leveraging causal inference and machine learning to analyze large-scale datasets. Complementing this, Thalia Viranda's extensive clinical research experience with populations exhibiting emotion dysregulation and deficits in self-control provides a deep understanding of symptom assessment methods, psychopathology, and the complexities of mental health symptomatology. Through this project, we aim to contribute insights that could support proactive, data-driven interventions to improve mental health outcomes in vulnerable professional groups.

1.2 Research Question and Hypotheses

RQ: Does the inclusion of graph-based features derived from networks of passive sensing and self-reported mental health data improve the accuracy of predicting suicidal ideation among medical residents compared to models using only individual-level features?

H_{01}: The inclusion of graph-based features (e.g., centrality, clustering coefficients) derived from networks of passive sensing and self-reported mental health data **does not improve** the accuracy of predicting suicidal ideation among medical residents compared to models using only individual-level features (e.g., raw scores from PHQ-9, GAD-7, and step count).

H_{a1}: The inclusion of graph-based features (e.g., centrality, clustering coefficients) derived from networks of passive sensing and self-reported mental health data **improves** the accuracy of predicting suicidal ideation among medical residents compared to models using only individual-level features (e.g., raw scores from PHQ-9, GAD-7, and step count).

2 Methods

2.1 Dataset Description

This study uses a multimodal dataset from the Intern Health Study (2018–2019 cohorts). The Intern Health Study is a longitudinal cohort study that assesses stress and mood among medical interns across the United States. Participants are enrolled at the start of their internship year and are followed throughout this period. Participants provide data through *a combination of self-reports and passive sensing*. **At baseline,** participants complete a comprehensive survey capturing demographic information, prior mental health history, and validated assessments such as the PHQ-9 for depression, GAD-7 for anxiety, and PC-PTSD-5 for PTSD. **Quarterly** follow-up surveys reassess mental health status using the same instruments and include *the Columbia-Suicide Severity Rating Scale (C-SSRS) to measure suicidal ideation*. **Daily mood ratings** are collected via a mobile app, while wearable devices continuously track objective behavioral data such as step count and sleep duration.

2.2 Data Science Workflow: Alignment with the PCS Framework

2.2.1 Data Cleaning

Thalia We will fill missing values for step count and sleep metrics using domain-specific imputations. For instance, for hours with sleep but no steps recorded (or vice versa), assign a value of 0 to missing variables (e.g., steps = 0 during sleep periods). Additionally, if multiple consecutive hours of data are missing, the gap will be flagged for participant-level data quality checks. We will drop points without mood rating for the past 24 hours, as these represent non-compliance with the daily ecological momentary assessments (EMAs).

Thalia + Alex Given the high variability and potential noise in both passive sensing and self-reported data, we will identify extreme values using Isolation Forest models. This approach allows us to systematically detect and address anomalies while preserving data integrity: (1) Perform anomaly detection independently for each feature (e.g., step count, mood ratings) to ensure accurate identification of outliers specific to the context of each data type; (2) Detect and remove unrealistic outliers, such as implausible physical activity levels (e.g., walking 20,000 steps in an hour) or missing data misrepresented as zeros (e.g., 0 hours of sleep when a device failed to record); (3) Retain behaviorally meaningful outliers that reflect genuine deviations in patterns, such as abnormally long sleep durations or unusually low step counts, which may indicate depressive episodes or other mental health challenges. By filtering out extreme but unrealistic data while preserving significant behavioral deviations, this step ensures that downstream analyses focus on meaningful patterns rather than noise or artifacts.

Alex We will filter participants with insufficient data coverage, such as excluding individuals with less than 100 total hours of data across the study period to maintain reliability, and removing participants whose data shows zero variance for any key feature (e.g., constant step count or mood ratings). For temporal alignment, we will aggregate daily passive sensing data (e.g., average step count, mood ratings) to align with the quarterly suicidal ideation assessments (C-SSRS). We also will compute additional behavioral indicators such as, sleep variability (standard deviation of sleep duration), mood variability (standard deviation of mood ratings), and proportions of sedentary vs. active periods

2.2.2 Network-Based Predictive Modeling Framework

Thalia + Alex To predict suicidal ideation, we will construct symptom-behavior networks and use graph-derived features in machine learning models. Data will be segmented into two groups: an at-risk group (quarters immediately preceding a suicidal ideation event, C-SSRS positive) and a control group (quarters with no reported suicidal ideation). Networks will include features from both passive sensing data (e.g., step count, sleep duration) and self-reported symptoms (e.g., daily mood ratings, PHQ-9, and GAD-7 items). Nodes will represent behavioral and symptom metrics, while edges capture relationships using correlation measures (e.g., Pearson, Spearman). Separate networks for at-risk and no-risk groups will be analyzed and compared based on structural properties, such as degree centrality and clustering coefficients, to identify differences in symptom connectivity linked to suicide risk.

Alex Feature engineering will extract graph-derived metrics from these networks, including degree centrality (key symptoms or behaviors), clustering coefficients (local connectivity patterns), and shortest path lengths (efficiency of information transfer). These features will be combined with traditional predictors, such as aggregated behavioral data (e.g., average step count, sleep duration) and validated self-report scores (e.g., PHQ-9, GAD-7), to create a comprehensive dataset for modeling.

Thalia + Alex The primary outcome for predictive modeling will be suicidal ideation (binary: 1 = ideation present, 0 = ideation absent), with continuous C-SSRS severity scores used for secondary analyses. Models will be trained on 2018 data and tested on 2019 data to ensure robustness and generalizability. Logistic regression will provide interpretable insights into key predictors, while random forests and gradient boosting models will address non-linear relationships and complex feature interactions. This approach evaluates the added predictive value of network-based features alongside traditional predictors. To ensure reliability, we will use stratified k-fold cross-validation to address class imbalance (e.g., fewer suicidal ideation instances). Performance metrics tailored for imbalanced datasets will include AUC-ROC (overall performance), precision-recall curves (sensitivity to true positives), and the F1-score (balancing precision and recall). Finally, statistical analyses will compare models with and without graph-derived metrics to assess their contributions to accuracy, while tools like SHAP (Shapley Additive Explanations) will identify and interpret key features, providing actionable insights into symptom-behavior relationships driving suicide risk.

Thalia + Alex Results from our analyses will be presented in the class presentation and the final paper for this project.

Project Github Repository This project's drafted github repository can be found here

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