**IEEE CS Bangalore Chapter Internship and Mentorship Program - 2025**

**Duration: 1st April 2025 to 30th September 2025**

**Monthly Progress Report Template**

**Project ID: P18**

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**Title of the Project: Digital Phenotyping for Early Detection of Student**

**Stress**

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Digital Phenotyping for Early Detection of Student Stress

Monthly Report – May

# Executive Summary of Progress

In April, our team laid down the foundation for the StressSense system. We finalized the development of the cross-platform mobile app using Flutter, which included crafting the UI, integrating passive data collection mechanisms like accelerometer and GPS, and establishing a Firebase backend that securely stored real-time data. On the web side, we created a robust admin dashboard using Firebase and a frontend framework that allows the mentor or admin to analyze cohort data, visualize sensor activity via heatmaps, and export CSV files for further analysis. We also created a simple prototype of our machine learning pipeline. This involved capturing mock sensor data, processing it into usable features using a Python-based script, and passing it through a basic SVM (Support Vector Machine) model trained on synthetic datasets. The purpose of this was to validate the flow from sensor data to stress prediction output.

During May, we expanded significantly beyond initial implementation. Our focus shifted towards preparing the system for real-world deployment. This included legal and privacy frameworks required for real user data collection. We drafted user consent forms that align with GDPR and HIPAA regulations, including details about how data will be stored, used, and shared. We also began the process of submitting documents to the Institutional Review Board (IRB) to ensure ethical compliance during the pilot phase. From a technical standpoint, we worked on integrating OAuth-based authentication for third-party health services like Fitbit and Apple HealthKit. These services allow us to collect heart rate and step count data directly from wearables, thereby increasing the quality and resolution of physiological data. Data from these services was routed securely through Firebase Cloud Functions and stored with encryption. We deployed a pilot version (v0.9) of the app to 20 students. Out of those, 18 students successfully onboarded and 16 of them completed their first round of surveys (PSS and DASS-21). We set up automated alerts in case any sensor fails to report, and this helped us achieve 92% hourly data completeness for internal sensors and 85% for external ones. We also observed good engagement rates, with 14 students using the in-app chatbot daily.

Looking ahead to June and beyond, we aim to continue the pilot through at least mid-June. This will involve deploying mid-pilot surveys and comparing real survey responses with the system's stress predictions. We plan to retrain our model using the real data collected so far, and analyze its correlation with self-reported stress scores. Feedback collected from students will be used to enhance the user experience, particularly around clarity of permissions, notification frequency, and app performance. We will also work on the statistical side by building a toolkit that helps visualize trends in stress levels, performs paired t-tests between predicted and reported values, and generates basic reports. This will set the stage for drafting the final sections of our research article.

# 1. Problem Definition

The central issue our project addresses is the early identification of stress in university students using their smartphones. Academic stress often builds up silently and affects students' performance and mental health. Traditional methods such as paper-based surveys are reactive and infrequent. Our approach allows for continuous, passive, and privacy-conscious monitoring using the sensors already present in students' devices. The goal is to identify stress patterns as they emerge, enabling intervention before the situation worsens. Our app not only tracks physical movement and location but also introduces active input like mood check-ins through a chatbot to create a hybrid sensing framework. In May, we further refined our definition by understanding how passive data like reduced mobility or changes in sleep timing may be early signs of stress.

# 2. Literature Review

In April, we explored the existing body of work on digital phenotyping, including systems like StudentLife and mindLAMP. These projects showed us how smartphone data could be used to infer psychological states. In May, we dove deeper into research surrounding multimodal sensor fusion, which involves combining data streams from different sensors to make better predictions. We also studied the limitations of current models when deployed in real-world settings, especially regarding user dropout and missing data. We began comparing model validation techniques and started compiling a bibliography of studies that used survey-based and passive sensing methods together. This reinforced our confidence in combining both passive (sensor-based) and active (survey/chatbot-based) methods in our design.

# 3. Existing System

The systems we studied in April mostly lacked integration between administrative dashboards and the student-facing app. In May, we began benchmarking our own platform against these systems. We found that our architecture was more flexible, thanks to its modular design. While commercial tools often limit sensor access due to privacy concerns or rely on closed platforms, our open-source-like model gave us more control. We added the ability to collect data from both the phone and connected devices and sync this securely to our database. This gave us a clearer picture of student behavior in near real-time and filled some of the gaps that other systems leave unaddressed.

# 4. Proposed System

Our system was initially designed as a mobile app with a backend dashboard. In May, we added several new components:

* We built modular consent screens that appear dynamically depending on what sensors are being used (e.g., phone GPS or Fitbit heart rate).
* The OAuth connectors were tested and partially integrated with Fitbit and HealthKit, which allow users to link their wearable devices easily.
* The ingestion pipeline was modified to use Firebase Functions, which gave us flexibility in preprocessing data and ensured encrypted transmission.
* The admin dashboard now features real-time logs, user engagement summaries, and error tracking. Together, these improvements help us meet both technical and ethical requirements while preparing us for large-scale deployments in future versions.

# 5. Knowledge Gained – Tools, Technology, Courses etc.

This month was especially rich in learning. We completed multiple short courses and tutorials, including:

* A crash course on data privacy laws (GDPR and HIPAA).
* Firebase Cloud Functions documentation and OAuth authentication guides.
* Tutorials on integrating external APIs (like Fitbit’s Web API and HealthKit).
* Statistical modeling videos for paired t-tests and hypothesis testing, which we’ll use in our analysis phase. Apart from this, we also learned practical skills during the pilot—such as debugging installation issues, helping participants through onboarding, and managing Firebase logs and triggers efficiently.

# 6. Architectural Framework

The May version of our architecture added new layers:

* External API Layer: Handles third-party sensor streams with authorization and token management.
* Consent Control Module: Monitors what permissions are granted by users and alerts the admin if they revoke them.
* Anomaly Detection and Monitoring: Flags inactive users or broken sensors using Cloud Functions and triggers alerts via email or SMS. We also restructured our Firestore database to better accommodate time-series data, improving how we query user-specific trends across time.

# 7. Project Implementation

* Released version 0.9 of our mobile app with all core features.
* Integrated OAuth flows into settings for wearable login.
* Added chatbot improvements for daily check-ins and mental health tips.
* Enabled encrypted storage and server-side checks for data validity.
* Began long-term logging and backup routines in the backend.
* Supported 20 participants in the pilot launch and tracked live analytics. This implementation round made our app not just feature-complete but also reliable in real-world settings.

# 8. Results

* 90% of participants ***(Friends & Family)*** installed the app and used it at least once a day.
* More than 70% responded to at least two check-in chatbot prompts.
* We observed consistent passive data flow from both internal and external sensors.
* 16 of 20 completed both surveys on time.
* Pilot logs indicate system uptime of 98.6%, with minimal failures.
* We are seeing early evidence of correlations between increased sedentary time and higher reported stress. These results validate our design choices and show that the system performs well even without constant user interaction.

# 9. Conclusion and Future Work

As we transition from development to real-world validation, we feel confident in the robustness and usefulness of our app. May marked a major turning point where features gave way to insights. In June, we’ll continue to fine-tune our system based on user feedback, enhance statistical analysis, and improve the interface based on real usage patterns. This includes changing how notifications are timed, clarifying permissions, and tuning our ML models using actual data. We’re also excited to begin final preparations for our research article and plan the July wrap-up.

# 10. Research Article Preparation

We made a structured start in May by:

* Outlining the full article and defining its sections.
* Drafting Introduction and Methodology.
* Starting preliminary Results figures.
* Creating a shared folder for charts, plots, and scripts. We plan to have a working draft by the end of June.

Signature of the Mentor

Date: 14th June 2025