

# Data Processing Framework for Digital Health Monitoring using Roadmap 2.0

Aditya Jalin<sup>1,2</sup>, Rajnish Kumar<sup>3</sup>, Bengie L. Ortiz<sup>3</sup>, Xiao Cao<sup>3</sup>, Michelle Rozwadowski<sup>3</sup>, Muneesh Tewari<sup>2</sup>, Sung Won Choi<sup>3</sup>

### Background

Mobile health technologies offer unprecedented opportunities for longitudinal data collection in clinical research[1]. However, the vast amount and complexity of raw data generated pose significant challenges in data preprocessing, analysis, and reproducibility.

**Roadmap**, a mobile app for positive wellness-based psychology interventions<sup>[2]</sup>, was used to collect physiological and psychological data from bone marrow transplant (BMT) patientcaregiver dyads for up to 120 days post-transplant using Fitbit<sup>®</sup> Charge 3 devices

#### Sampling Data — Day 30 Dav 120 🕈 # Records Day 0 Modality Rate Surveys 526 3 timepoints 166 Dyad Every few Heart rate 5M+ seconds Sleep Every few 45K+ Patterns hours fitbit charge 3. Physical Every minute 450M+ Activity 20K+ Self reported Daily mood

Fig 1: Data Collection timeline. BMT transplant performed on Day 0,. Baseline PROMIS survey was performed the day after transplant, followed by additional surveys after 30 and 120 days. Fitbit<sup>®</sup> Charge 3 was used to collected heartrate, physical activity and sleep data of both patients and caregivers.

### **Objectives**

To develop a flexible, efficient, and standardized data processing pipeline for **Roadmap** that can

- Process multi-source digital health data
- Ensure data quality and reliability
- Maintain privacy and security
- Enable scalable analysis

### **Key Features**

1)

- Modular pipeline architecture
- Automated validation checks
- Flexible integration capabilities

## Aditya Jalin, BTech, MRes

adityabn@umich.edu Sung Won Choi, MD, MS

sungchoi@umich.edu

Hicks JL, Boswell MA, Althoff T, Crum AJ, Ku JP, Landay JA, Moya PML, Murnane EL, Snyder MP, King AC, Delp SL. Leveraging Mobile Technology for Public Health Promotion: A Multidisciplinary Perspective. Annu Rev Public Health. 2023 Apr 3;44:131-150. doi: 10.1146/annurev-publhealth-060220-041643. Epub 2022 Dec 21. PMID: 36542772; PMCID: PMC10523351 Rozwadowski M, Dittakavi M, Mazzoli A, Hassett AL, Braun T, Barton DL, et al.. Promoting health and well-being through mobile health technology (Roadmap 2.0) in family caregivers and patients undergoing hematopoietic stem ntation: Protocol for the development of a mobile randomized controlled trial. JMIR Res Protoc. JMIR Res Protoc; 2020; doi: 10.2196/19288 3) Bajwa J, Munir U, Nori A, Williams B. Artificial intelligence in healthcare: transforming the practice of medicine. Future Healthc J. 2021 Jul;8(2):e188-e194. doi: 10.7861/fhj.2021-0095. PMID: 34286183; PMCID: PMC8285156.

### Conclusions

The developed modular data processing - pipeline significantly enhances the efficiency and reproducibility of mobile health research using Roadmap 2.0 data. The pipeline addresses critical challenges in handling complex, multisource mobile health data. This approach not only streamlines data management throughout the research lifecycle but also sets a foundation for more advanced analytics, including the potential integration of machine learning techniques[3]

### References

### **Study Design**

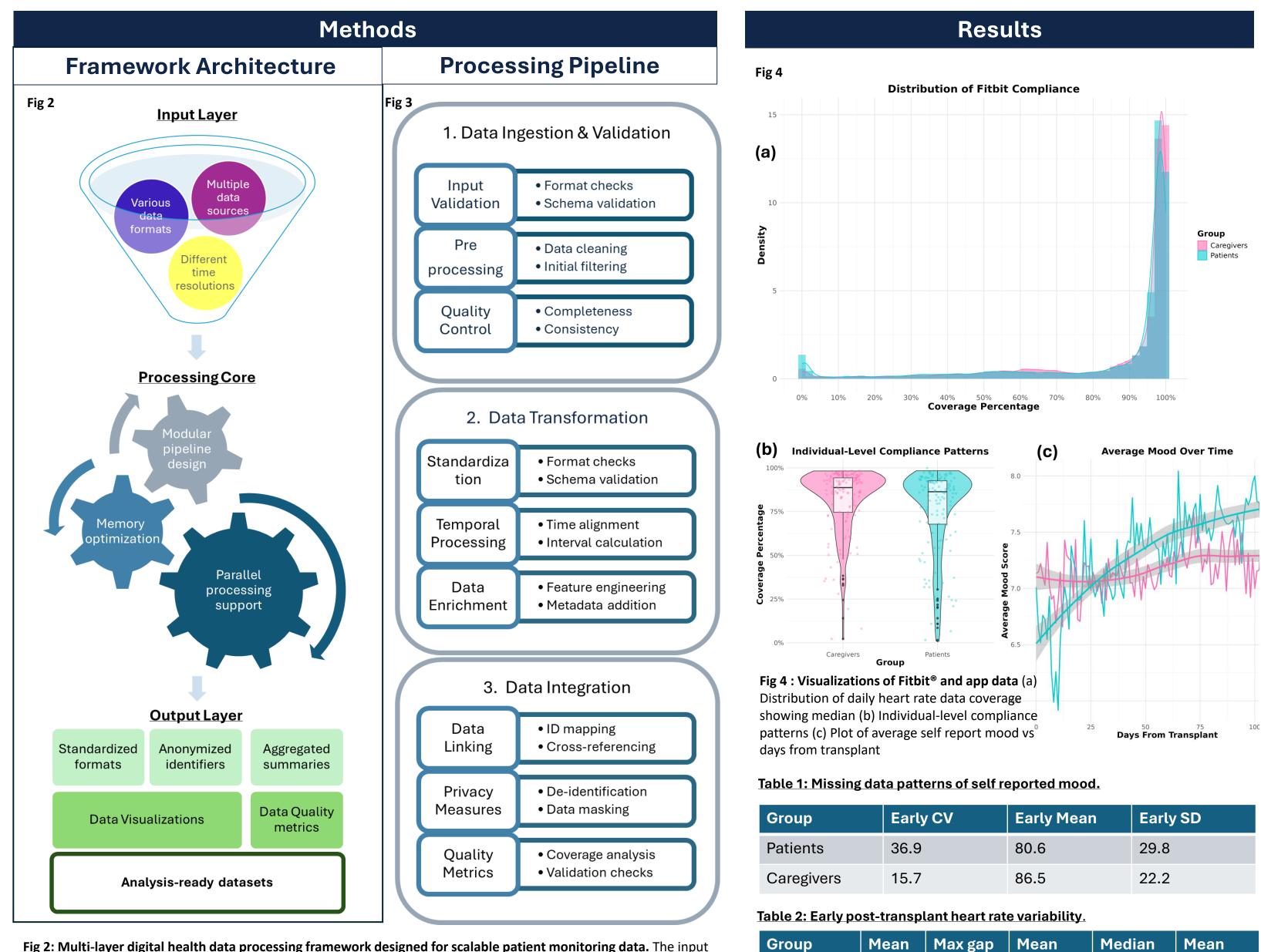


Fig 2: Multi-layer digital health data processing framework designed for scalable patient monitoring data. The input layer handles diverse data streams from wearable devices (Fitbit heart rate, sleep, activity), mobile applications (mood scores), and clinical records (EHR data). The processing core implements modular components for data validation, transformation, and integration with parallel processing capability for high-throughput analysis. The output layer produces standardized, analysis-ready datasets with comprehensive quality metrics and validation reports. Each layer maintains strict privacy controls and data integrity checks.

Fig 3: Three-stage data processing pipeline optimized for heterogeneous health monitoring data

- Department of Biostatistics, School of Public Health, University of Michigan

arly CV	Early Mean	Early SD
6.9	80.6	29.8
5.7	86.5	22.2

ו	Max gap length	Mean gap length	Median gap length	Mean days missed
	83	5.83	1	36.9
	89	4.31	1	39.9

#### Affiliations

tota

gaps

12.5

15.7

Patients

Caregivers

2. Department of Internal Medicine, Division of Hematology and Oncology, University of Michigan 3. Department of Pediatrics, Division of Pediatric Hematology Oncology, University of Michigan