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Interoperable Federated Access to Multi-Vendor Wearables for Postpartum Well-being Support: A Standards-Based Architecture for MAMAI

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Abstract: Postpartum depression is a serious challenge for maternal health, affecting mothers’ well-being, infant development and family stability. Although wearable devices and mobile sensing technologies can continuously collect physiological and behavioural data, most existing maternal health applications are limited to specific device ecosystems. This paper presents MAMAI (Maternal Assistance and Monitoring through Artificial Intelligence), an interoperable framework designed to support postpartum well-being monitoring by ingesting data from multiple wearable devices. The proposed system enables interoperability across different sensing platforms and healthcare infrastructures by integrating two standards: the Open Geospatial Consortium (OGC) SensorThings Application Programming Interface (API), which manages Internet-of-Things (IoT) sensor observations, and the Fast Healthcare Interoperability Resources (FHIR), which represents well-being indicators in clinically compatible formats. The system follows a three-layer edge–cloud architecture that performs local preprocessing of wearable signals, standardized data transformation, and cloud-based well-being analytics. One of the main outputs of the well-being analytics module is the composite well-being score. This score is calculated from normalized indicators derived from sleep patterns, physical activity, and heart-rate signals. By connecting consumer wearable devices with standardized healthcare data infrastructures, the proposed framework provides a scalable foundation for maternal digital health systems.

1. Introduction

1.1 Motivation and Problem Statement

Depression is one of the most widespread mental health disorders globally, affecting more than 332 million people worldwide and leading to significant health and societal burdens (World Health Organization, 2025). Among its various forms, postpartum depression represents a particularly critical public health concern due to its impact on maternal well-being, infant development, and overall family health outcomes. The postpartum period is associated with substantial physiological, psychological, and social changes that increase vulnerability to mental health disorders. In Canada, approximately 49% of mothers and birthing parents reported symptoms consistent with postpartum depression or anxiety, with 60% beginning after childbirth (Statistics Canada, 2026). Improving early detection and continuous monitoring of postpartum symptoms has therefore become an important priority for healthcare systems and digital health research (Wang et al., 2025; Zhang et al., 2025; Alkhateeb et al., 2026).

Traditional clinical assessment of depression typically relies on clinician-administered or self-reported screening instruments. Although these tools are clinically validated, they are usually administered infrequently and therefore fail to capture short-term fluctuations and temporal dynamics in postpartum symptoms (Chikersal et al., 2021; Alkhateeb et al., 2026). In addition, retrospective self-report methods are susceptible to recall bias and socially desirable responses, which may reduce the reliability of reported symptoms (Chen et al., 2023).

Recent advances in mobile sensing and wearable technologies offer new opportunities for unobtrusive, continuous monitoring of behavioural and physiological signals related to mental well-being. Smartphones and wearable devices can collect longitudinal data streams such as heart rate variability, sleep patterns, and physical activity levels, which may reflect changes in emotional and cognitive states (Moshe et al., 2021; Mohr et al., 2024). Passive sensing approaches therefore offer a promising direction for complementing traditional mental health assessments by enabling continuous observation of real-world behavioural patterns and physiological signals (Torous et al., 2021; Torous et al., 2026).

Despite the growing availability of wearable devices capable of continuously measuring heart rate, sleep, and physical activity, their integration into maternal healthcare monitoring remains limited (Ajayi et al., 2025; Sezgın et al., 2023; Wang et al., 2025). A key barrier is that physiological data from wearable devices are stored within vendor-specific platforms, making it difficult to integrate data across devices and into clinical workflows.

In addition, the management of sensitive physiological and mental health data raises concerns regarding privacy, trust, and user autonomy, as individuals may hesitate to share biosignal data without clear mechanisms for consent and secure data handling (Zadushlivy et al., 2025). Bridging this gap requires not only technical interoperability across device ecosystems but also alignment with standardized clinical data infrastructures (Xie et al., 2021). The Fast Healthcare Interoperability Resources (FHIR), an internationally recognized standard for the exchange of healthcare information, provides a structured framework for representing and transmitting maternal health data in a format compatible with existing clinical systems (HL7 International, 2023). However, maternal-care-specific data models within FHIR remain underdeveloped, and the mapping of wearable-derived biosignals to FHIR-compliant resources has received limited attention in the digital maternal health literature—representing a gap this work directly addresses.

1.2 Research Contributions

Through this dual-standard architecture, MAMAI (Maternal Assistance and Monitoring through Artificial Intelligence) is designed to enable federated access to multi-vendor wearable devices while ensuring seamless integration with healthcare monitoring infrastructures. By bridging proprietary sensing ecosystems with standardized clinical information systems, the framework supports interoperable and scalable data exchange across heterogeneous platforms.

The main contributions of this work are as follows. First, we present a standardized data integration pipeline that transforms heterogeneous wearable sensor outputs into structured, clinically compatible data models grounded in the Open Geospatial Consortium (OGC) SensorThings Application Programming Interface (API) and Health Level Seven (HL7) FHIR, ensuring semantic consistency and cross-platform interoperability. Second, we demonstrate a device-agnostic harmonization framework that unifies physiological signals — including sleep, physical activity, and heart rate — from multi-vendor wearable devices into a single interoperable representation, enabling scalable data exchange across heterogeneous sensing platforms. Third, we introduce a composite postpartum well-being score derived from these harmonized physiological indicators, operationalized as a continuous and clinically interpretable metric designed to support longitudinal maternal health monitoring and inform care decisions within FHIR-compatible healthcare infrastructures.

1.3 Related work

The use of smartphones and wearable devices for passive monitoring of behavioural and physiological signals associated with mental health has grown substantially over the past decade. Early platforms established the feasibility of continuous, unobtrusive data collection in everyday settings, while more recent work has progressively incorporated richer physiological sensing and machine learning-based inference. Despite this progress, significant gaps remain — particularly with respect to clinical interoperability, maternal health contexts, and cross-device data integration. Table 1 presents digital health platforms that leverage mobile sensing and wearable technologies to monitor behavioural and physiological indicators associated with mental health, including more recent applications in maternal and postpartum contexts.

Early work, such as BeWell (Lane et al., 2011), introduced smartphone-based monitoring of behavioural indicators, including sleep duration, social interaction, and physical activity using built-in mobile sensors. The main advantage of this system was its ability to perform passive behavioural monitoring without requiring additional wearable devices. However, the platform relied primarily on smartphone sensors and therefore lacked access to physiological signals such as heart rate variability, which limits its ability to capture deeper physiological indicators of mental health.

Later studies expanded this concept through large-scale behavioural monitoring systems. StudentLife (Wang et al., 2025) investigated student mental health by collecting smartphone sensor data related to mobility, activity levels, stress, and sleep behaviour. One strength of this study was the large-scale longitudinal data collection that enabled detailed behavioural analysis of daily life patterns. However, the system focused primarily on smartphone-derived behavioural signals and did not incorporate wearable physiological sensing, which may provide additional insights into emotional and physiological states.

Similarly, the Beiwe Platform (Torous et al., 2016) provided an open-source infrastructure for digital phenotyping research, enabling continuous collection of behavioural signals such as mobility patterns, communication behaviour, and sleep indicators from smartphones. The open-source design of Beiwe

Table 1. Comparison of representative mobile sensing, wearable, and maternal-monitoring platforms with respect to interoperability and maternal-health relevance

Platform / Study	Primary use case and technology	Main indicators	Interoperability / standards support	Maternal or postpartum specific
BeWell (Lane et al., 2011)	Smartphone-based behavioural monitoring	Sleep duration, physical activity, social interaction	No explicit clinical interoperability; research-oriented mobile sensing framework	No
StudentLife (Wang et al., 2014)	Smartphone-based behavioural and mental health monitoring	Sleep patterns, stress, physical activity	No explicit clinical interoperability; research platform	No
Beiwe Platform (Torous et al., 2016)	Digital phenotyping research for mental health	Mobility patterns, sleep, communication behaviour, sleep indicators	Open-source research infrastructure, but limited standardized exchange with clinical systems	No
RADAR-Base (Ranjan et al., 2019)	Smartphone and wearable fusion for remote monitoring of depression and chronic disease	Sleep, heart rate, activity	Supports open-source mHealth platform & multimodal collection, but limited direct integration with clinical standards such as HL7 FHIR	No
Mood and Digital Biomarkers (Abdullah et al., 2022; Moshe et al., 2021)	Depression detection using multimodal sensing (smartphones, wearables)	Mood ratings, sleep, activity, phone usage, mobility	Primarily study-specific analytics pipeline; limited multi-vendor and clinical interoperability	No
Maternal wearable monitoring review (Alim et al., 2023)	Review of wearable sensing for pregnancy and maternal health	Maternal activity, physiological monitoring, fetal/maternal health signals	Evidence of growing wearable use, but systems are heterogeneous and often not deployed through interoperable clinical architectures	Yes, pregnancy
Consumer wearable biomarkers for postpartum depression (Hurwitz et al., 2024)	Postpartum depression recognition using consumer wearables	Heart rate, physical activity, energy expenditure, postpartum digital biomarkers	Demonstrates promise of consumer wearables, but not presented as a standards-based interoperable care platform	Yes, postpartum
Pregnancy digital phenotyping protocol(Glime et al., 2025)	Continuous pregnancy and postpartum monitoring	Behavioural, physiological, and contextual signals π	Pregnancy-specific multimodal design, but still a research protocol rather than an interoperable clinical integration framework	Yes, pregnancy & postpartum
Proposed MAMAI framework	Interoperable postpartum well-being monitoring	including sleep, physical activity, and heart rate	Designed for standards-based interoperability using OGC SensorThings API and HL7 FHIR-compatible representations	Yes, postpartum

allows researchers to conduct large-scale mental health studies with flexible data collection pipelines. Nevertheless, the platform primarily focuses on research data collection and does not provide standardized interoperability mechanisms for integration with healthcare information systems.

More recent platforms have integrated wearable devices to capture physiological signals alongside behavioural data. RADAR-Base (Ranjan et al., 2019) introduced an open-source mHealth platform designed for monitoring of depression and other chronic diseases by combining smartphone with wearable devices such as Fitbit to collect heart rate, sleep, and activity measurements. The integration of wearable sensors represents an important advancement compared with earlier smartphone-only platforms. However, interoperability with clinical healthcare systems remains limited, and integration with standardized healthcare data models such as HL7 FHIR is not fully supported.

More recently, studies such as Mood and Digital Biomarkers (Abdullah et al., 2022) have explored multimodal sensing approaches that combine smartphone data with wearable devices such as the Oura Ring to detect depressive symptoms using machine learning models (Moshe et al., 2021). These approaches demonstrate strong potential for detecting mental health indicators by leveraging both behavioural and physiological signals. However, many such systems rely on proprietary sensing ecosystems and study-specific machine-learning pipelines, which can limit interoperability and hinder deployment within broader healthcare infrastructures.

Building on these advancements, recent research has increasingly focused on maternal and postpartum health monitoring using wearable technologies. The review by Alim et al. (2023) highlights the expanding use of wearable sensing for pregnancy, capturing maternal activity, physiological signals, and fatal–maternal health indicators. While this work demonstrates the growing importance of wearables in maternal care, it also shows that existing systems are highly heterogeneous and rarely implemented within interoperable clinical architectures. Similarly, Hurwitz et al. (2024) explore consumer wearable biomarkers for postpartum depression detection using indicators such as heart rate, physical activity, and energy expenditure, illustrating the potential of wearable-based postpartum monitoring, yet lacking integration with standardized clinical systems. Furthermore, Glime et al. (2025) propose a pregnancy digital phenotyping protocol that enables continuous monitoring of behavioural, physiological, and contextual signals from late pregnancy through the postpartum period. Although this approach provides a comprehensive multimodal framework, it remains primarily research-oriented and is not integrated into interoperable healthcare infrastructures.

The literature has evolved from smartphone-based behavioral monitoring toward multimodal sensing approaches that incorporate consumer-grade wearables, and more recently, studies focused on pregnancy and postpartum populations. Despite this progress, existing solutions remain largely fragmented, often confined to research-specific pipelines or proprietary device ecosystems. Interoperability with clinical information systems is rarely addressed, and dedicated support for postpartum care remains limited.

These limitations highlight a critical gap, which motivates the proposed MAMAI framework—designed to enable maternal-specific monitoring while facilitating multi-vendor wearable integration and standards-based clinical data exchange.

2. System Architecture and Design

This section presents the overall architecture of the proposed MAMAI framework, describing how multi-vendor wearable data are accessed in a federated manner, standardized, and processed to support maternal well-being monitoring. The framework is designed to enable interoperable integration of heterogeneous wearable data sources within a unified system. Section 2.1 introduces the federated data access model, which allows users to securely connect their wearable devices while maintaining control over their personal health data. Section 2.2 describes the interoperability layer, focusing on the use of OGC SensorThings API for managing sensor observations in Internet-of-Things (IoT) environments and HL7 FHIR for representing well-being indicators in clinically interoperable formats. Subsections 2.2.1, 2.2.2, and 2.2.3 provide detailed descriptions of these standards and the interoperability mapping of maternal well-being indicators. Finally, Section 2.3 presents the three-layer edge–cloud architecture, outlining how data are collected, pre-processed at the edge, transformed into standardized formats in the cloud, and delivered to a user-facing platform for visualization and analysis.

2.1 Federated Data Access Model

To preserve privacy while supporting cross-platform integration, MAMAI adopts a federated data access model in which sensitive raw data are not routinely centralized. Continuous source data generated by wearables and health applications, including physiological signals, sleep records, and activity traces, remain on the user’s device or under the control of the source platform by default. Local edge processing transforms these inputs into derived maternal well-being indicators, including stress-related Heart Rate Variability (HRV) measures, sleep quality summaries, and activity-based behavioural metrics.

The system transmits only the minimum necessary outputs of this local processing, namely summarized indicators, timestamps, provenance metadata, and other standardized observations required for downstream integration. Within the central cloud environment, MAMAI stores these normalized records, associated consent and access metadata, and FHIR-compatible resources for dashboard delivery and optional clinical interoperability, while avoiding persistent storage of raw continuous streams The architecture defines a clear data boundary between local raw-data retention, local feature derivation, selective transmission, and minimal central storage. In practical terms, raw signals stay local; features are computed locally; summaries are transmitted by user permission; standardized records are stored centrally.

2.2 Interoperability Standards

This section presents the interoperability framework of the proposed system, focusing on the standardization and integration of heterogeneous wearable data. It introduces the OGC SensorThings API and HL7 FHIR standards, followed by the mapping of maternal well-being indicators to enable consistent representation across IoT and healthcare domains.

2.2.1 OGC SensorThings API

The OGC SensorThings API (STA) is an open interoperability standard developed by the OGC to support the structured management, discovery, and exchange of observations generated by distributed IoT sensing devices (Liang et al., 2016). The standard provides a Representational State Transfer (REST)-ful service interface and a lightweight data representation model, enabling sensor observations to be exchanged using widely adopted web technologies such as Hypertext Transfer Protocol (HTTP) and JavaScript Object Notation (JSON). Designed for scalable IoT environments, the STA supports real-time access, querying, and integration of sensor-generated observations across distributed sensing infrastructures. By defining a unified data model for sensors, observations, and associated metadata, the standard facilitates interoperability across heterogeneous sensing platforms and simplifies integration of multi-source sensor data. The STA data model represents sensing environments through several core entities, including Thing, Sensor, ObservedProperty, Datastream, and Observation (Liang et al., 2016).

Within the MAMAI framework, the STA is used to structure physiological signals collected from heterogeneous wearable devices across users. These devices capture key maternal well-being indicators, including sleep patterns, physical activity, and cardiovascular signals such as heart rate and heart rate variability. Representing these measurements using the standardized SensorThings data model enables consistent ingestion, storage, and management of wearable sensor observations from multiple vendors. This approach enhances interoperability across wearable ecosystems while supporting scalable processing of continuous physiological data. For example, a *Thing* represents the physical device (e.g., a smartwatch), while a *Sensor* describes the measurement component associated with that device. An *ObservedProperty* defines the phenomenon being measured, such as sleep duration, step count, or heart rate variability. A *Datastream* organizes observations of a specific property into a time-series structure, and an *Observation* represents an individual measurement with an associated timestamp and unit. For instance, a heart rate reading from a smartwatch can be represented through this entity chain, linking the device, sensing mechanism, measured property, and recorded value.

2.2.2 HL7 FHIR

The FHIR standard provides a modern framework for exchanging healthcare information between clinical systems, mobile applications, and health devices. Developed by HL7, FHIR defines a set of modular data structures known as resources that represent core healthcare entities such as patients, observations, devices, and clinical measurements. These resources can be exchanged using standardized REST Application Programming Interfaces (APIs) and widely adopted web formats such as JSON or Extensible Markup Language (XML), enabling efficient integration across heterogeneous health information systems (Mandel et al., 2016).

FHIR has been widely adopted as a global interoperability standard for healthcare data exchange, particularly in applications that integrate patient-generated health data from wearable devices and mobile health platforms. By providing a consistent representation of clinical observations, FHIR enables wearable-derived physiological signals to be integrated into Electronic Health Record (EHR) systems, clinical decision support tools, and research infrastructures (HL7 International, 2023).

Within the MAMAI architecture, the HL7 FHIR standard is used to represent wearable-derived well-being indicators in a clinically interoperable format. After wearable sensor observations are structured using the OGC STA, the resulting data streams are mapped to corresponding FHIR Observation resources. Each Observation resource captures key attributes, including the measured value, timestamp, unit, and references to the associated patient or device. Through this mapping, indicators such as sleep quality, activity level, and heart-function metrics are expressed as standardized clinical observations suitable for integration with healthcare systems.

FHIR further supports semantic interoperability by enabling consistent interpretation of wearable-derived indicators across different clinical platforms through standardized descriptors (HL7 International, 2023). By incorporating FHIR within the interoperability layer, MAMAI enables seamless integration of wearable-derived data with health records, research systems, and digital health applications, supporting scalable maternal health monitoring.

2.2.3. Interoperability mapping of maternal well-being indicators

To support cross-device aggregation, MAMAI maps heterogeneous vendor-specific measurements into a unified set of normalized maternal well-being indicators before exposing them through both OGC SensorThings and HL7 FHIR. This mapping layer reduces differences in naming, structure, and sampling granularity across platforms such as Apple Health, Fitbit, and Garmin.

For each measurement, the system defines the original vendor metric, the corresponding normalized indicator, its representation as a SensorThings Observation linked to a Datastream and Thing, and its equivalent FHIR resource element for downstream integration. Units and update frequency are also standardized to ensure consistency and reproducibility. Table 2 presents a subset of wearable-derived indicators and their representations across both interoperability standards.

In this process, vendor-specific measurements are normalized into platform-independent indicators and represented simultaneously as SensorThings Observations and FHIR Observation resources. This dual mapping enables consistent integration across wearable ecosystems while supporting downstream use in analytics, dashboards, and clinical workflows. Standardizing units and update intervals further improves comparability and traceability across devices with varying data structures, sampling behaviours, and data representations, ensuring consistent interpretation and integration of heterogeneous data.

Table 2. Mapping of wearable-based well-being indicators

Vendor metric	Normalized indicator	SensorThings entity	FHIR resource / code	Unit	Sampling
Heart rate variability (RMSSD/SDNN)	Stress / HRV indicator	Observation in HRV Datastream linked to maternal *Thing*	Observation.code = HRV	ms	Daily / recovery session
Resting heart rate	Cardiovascular indicator	Observation in Heart Rate Datastream	Observation.code = resting heart rate	beats/min	Daily
Sleep (duration + quality)	Sleep indicator	Observation in Sleep Datastream	Observation.code = sleep assessment	hours / score	Daily
Step count	Physical activity indicator	Observation in Activity Datastream	Observation.code = steps	steps/day	Daily

2.3 Three-Layer Edge–Cloud Architecture

The proposed system follows a three-layer edge–cloud architecture designed to transform maternal well-being data collected from wearable sensors into actionable insights. The architecture integrates heterogeneous wearable devices with secure cloud infrastructure and user-facing applications. Each layer performs a specific role within the data pipeline, including data acquisition, preprocessing, analysis, and visualization. By distributing computation across edge devices and cloud services, the architecture improves scalability and interoperability while enabling efficient management of wearable health data, as illustrated in Figure 1.

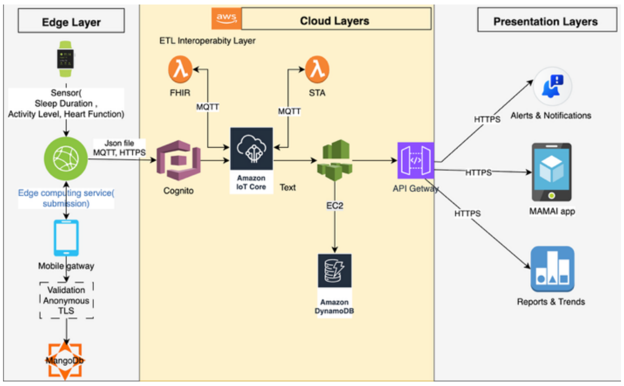


Figure 1: Federated interoperability data pipeline.

The edge layer receives physiological signals generated by multi-vendor wearable devices, including multi-vendor consumer smartwatches and clinical-grade wearable sensors. These devices continuously collect biosignals related to maternal well-being, including sleep patterns, physical activity metrics, and cardiovascular indicators such as heart rate or heart rate variability (Hartmann et al., 2019; Moshe et al., 2021). The wearable data are transmitted to the MAMAI application, where several preprocessing tasks are performed locally on the user’s device. These tasks include signal validation, noise filtering, feature extraction, and summarizing raw sensor readings into wellness indicators. Performing preprocessing at the edge reduces data transmission requirements while protecting sensitive physiological signals. A validation mechanism ensures that only reliable data are forwarded to the cloud layer. If collected signals do not meet validation criteria, they are discarded, preventing low-quality or erroneous data from entering the analysis pipeline. This edge-based validation improves system reliability and reduces unnecessary cloud processing. After preprocessing, the summarized indicators are anonymized and securely transmitted using encrypted communication protocols (e.g. Transport Layer Security (TLS)). The validated data are formatted as JSON records containing derived wellness indicators, including sleep quality, activity level, and heart-function metrics. Before transmission, user authentication and authorization are verified to ensure secure data sharing. The final output of the edge layer consists of encrypted wellness summaries, which are securely transmitted to the cloud infrastructure for further processing and analysis.
The cloud layer receives encrypted wellness summaries transmitted from the edge layer through secure communication channels. These summaries contain validated physiological indicators derived from wearable observations. Data ingestion is managed through an IoT message broker (e.g., Amazon Web Services (AWS) IoT Core) and an authentication and identity management service (e.g., AWS Cognito), which provide secure device connectivity, authentication, and access control. Once the data arrives in the cloud environment, an event-driven Extract, Transform, and Load (ETL) pipeline processes the incoming summaries and converts them into standardized data formats. Within the data pipeline, the data are transformed according to two interoperability standards—namely, the OGC STA and HL7 FHIR—as detailed in Table 2.
The presentation layer is used to deliver processed well-being insights and supports efficient access to analysed data through user-facing interfaces. The standardized outputs generated from the system are presented through interactive dashboards and visualization tools, enabling structured and intuitive access to wearable-derived health information. In this layer, wellness indicators derived from wearable sensors are displayed in a user-friendly format, supporting interpretation and integration with healthcare-related platforms such as monitoring dashboards or reporting systems. Although the underlying data originates from interoperable standards such as the STA and HL7 FHIR, this layer focuses on presenting the results in a clear and accessible manner, ensuring that users can effectively understand and utilize the well-being information.

3. Well-being Analytics

This section describes the analytics component of the proposed framework, which processes standardized wearable sensor data to derive interpretable well-being indicators. After interoperability mapping through OGC STA and HL7 FHIR, the resulting FHIR-formatted data are forwarded to cloud-based analytics services for further processing and interpretation.
The analytics module focuses on transforming physiological and behavioural signals into meaningful indicators that reflect maternal well-being. By leveraging standardized representations of wearable data, the system ensures consistency across heterogeneous device sources while enabling scalable and continuous monitoring.

3.1 Indicator Selection and Rationale

The selection of well-being indicators is guided by established findings in digital health research. Prior studies have consistently identified sleep patterns, physical activity, and HRV as key indicators associated with mental health status and stress levels (Abdullah et al., 2022; Hartmann et al., 2019). These indicators provide complementary insights into behavioural and physiological aspects of maternal wellbeing, supporting their use in continuous monitoring frameworks.
Based on these findings, the system utilizes three primary indicators: Sleep Quality (S), Physical Activity Level (A), and HRV-based indicators (H). These indicators capture complementary dimensions of maternal health, including recovery, behavioural patterns, and physiological stress. Sleep quality is derived from wearable-based measurements such as sleep duration and sleep efficiency. Physical activity is assessed using metrics such as daily step count or movement intensity. HRV-based indicators are obtained from cardiovascular signals and reflect autonomic nervous system regulation and stress response. To ensure comparability across heterogeneous wearable devices, all indicators are normalized to a standardized scale ranging from 0 to 100.

3.2 Composite Well-being Score

The composite well-being score is computed by aggregating the normalized indicators defined in Section 3.1. Let S, A, and Hdenote the normalized sleep, activity, and HRV-based scores, respectively.

$$S = (\text{SleepDuration} / \text{RecommendedSleep}) \times 100 \qquad (1)$$

where RecommendedSleep corresponds to clinically recommended sleep duration values. Physical activity is evaluated using wearable activity metrics such as daily step counts or movement intensity. Activity patterns have been widely used as indicators of behavioural well-being and lifestyle health in large-scale wearable sensing studies (Abdullah et al., 2022). The activity score is calculated as:

$$A = (Steps\ /\ RecommendedSteps) \times 100 \tag{2}$$

where RecommendedSteps represents a predefined activity threshold. HRV-based indicators capture physiological stress and recovery states through wearable-derived cardiovascular metrics such as resting heart rate or HRV. HRV has been widely used as a physiological marker of stress and autonomic nervous system balance (Hartmann et al., 2019). The normalized HRV-based score is defined as:

$$H = (HRV\ /\ HRV\_baseline) \times 100 \tag{3}$$

where $HRV_{baseline}$ represents an individualized baseline HRV value. The overall well-being score (WB) is computed as a weighted aggregation of the normalized physiological indicators:

$$WB = w_1 S + w_2 A + w_3 H \tag{4}$$

where S, A, and Hcorrespond to the normalized sleep, activity, and heart-function scores defined in Equations (1)– (3), and w_1, w_2, and $w_3$denote configurable weights controlling the contribution of each indicator.
equal weights are assigned to each indicator:

$$(w_1 = w_2 = w_3 = \tfrac{1}{3}) \tag{5}$$

To provide a balanced estimation of overall well-being, equal weights are assigned to each indicator. This approach follows questionnaire-based assessment methods, where multiple dimensions contribute equally to the overall evaluation and no single factor is assumed to dominate the final score. Multi-indicator aggregation strategies have been used in mobile sensing frameworks such as the BeWell platform, which combines behavioural indicators to generate a unified well-being score (Lane et al., 2011; Lane et al., 2015; Abdullah et al., 2022).

4. Implementation

This section presents the implementation of the proposed MAMAI framework and demonstrates its operational functionality through a working prototype. The prototype is implemented as a three-layer edge–cloud architecture that integrates federated wearable data access with standardized interoperability mechanisms based on the OGC STA and HL7 FHIR. The implementation supports end-to-end data flow, from edge-layer preprocessing to cloud-based transformation and presentation-layer visualization.

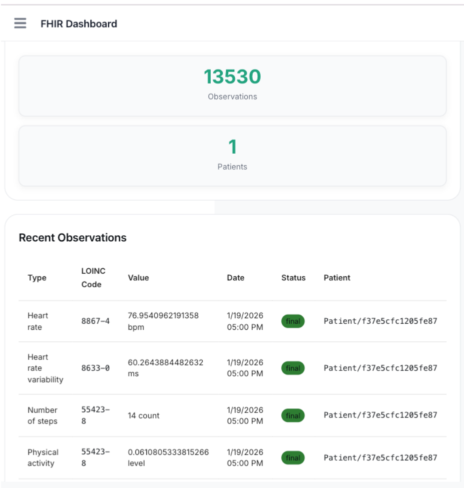
The system enables structured ingestion, standardization, and visualization of wearable-derived well-being indicators, as demonstrated through the SensorThings dashboard interface and user-facing monitoring views. Section 4.1 describes the prototype implementation, including system deployment, data processing pipeline, and integration of interoperability standards. Section 4.2 presents a functional validation of the prototype, focusing on verifying the end-to-end operation of the architecture and demonstrating the successful transformation, interoperability mapping, and visualization of wearable-derived indicators.

4.1 Prototype Implementation

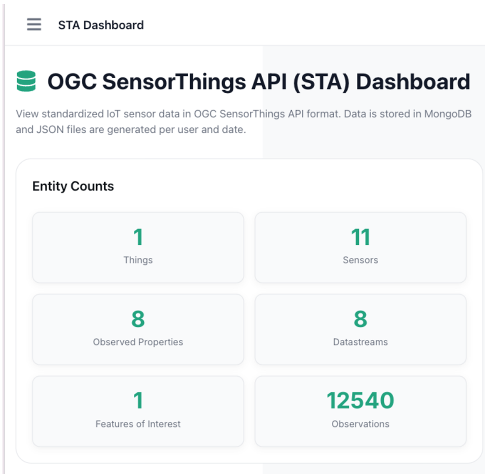
To validate the proposed architecture, a preliminary prototype of the MAMAI system was implemented and deployed across the full three-layer edge–cloud pipeline, including edge-layer preprocessing, cloud-based ingestion and transformation, and presentation-layer visualization. A synthetic physiological dataset was generated to emulate measurements generated by commercial smartwatches and fitness wearables. The dataset consisted of time-series sensor observations spanning multiple consecutive days of monitoring, covering three primary indicator streams: sleep duration, daily step count, and HRV. Observation values were parameterized to reflect realistic postpartum conditions, including reduced sleep efficiency, variable physical activity levels, and HRV patterns associated with early postpartum recovery.

The prototype system integrates heterogeneous wearable data sources through a federated access architecture, where data are processed locally at the edge and summarized well-being are transmitted to the cloud. At the edge layer, preprocessing tasks—including signal validation, noise filtering, feature extraction, and transformation into well-being indicators—are performed on the user’s device. This design reduces data transmission overhead while preserving privacy by avoiding centralized storage of raw physiological signals.

The interoperability mapping between wearable sensor data and standardized data models is illustrated in Figure 2.



(a)



(b)

Figure 2. Screenshot of the emulated MAMAI application. a) panel shows the mobile application interface, and b) panel shows the mapping of wearable sensor data to FHIR Observation resources and the SensorThings API (STA)

At the cloud layer, incoming data is securely transmitted via an IoT message broker (e.g., AWS IoT Core) and processed through an event-driven ETL pipeline. The data are transformed into standardized formats using two interoperability standards: the OGC STA for managing IoT sensor observations and HL7 FHIR for representing clinically interoperable well-being indicators.

The end-to-end pipeline latency was evaluated across all processing stages, focusing on both absolute and relative latency contributions. Under a fixed configuration, edge-layer preprocessing required approximately *0.6 s* per observation batch. Cloud-side transmission, ingestion, and ETL transformation into OGC STA and FHIR formats added approximately 1.1 seconds, followed by *0.5 s* for visualization, resulting in a total end-to-end latency of approximately *2.2 s* .

The evaluation was conducted using a consistent system configuration: a batch size of 75 observations, AWS Lambda with 1024 MB memory and concurrency of 10, edge devices with a quad-core CPU and 4 GB RAM, and a mid-tier EC2 instance (t3.medium). Each processing stage was measured under this same configuration to ensure comparability. Under these conditions, analyzing the relative latency of mapping nodes enables identification of bottlenecks and supports scalability optimization.

4.2 Prototype Validation

The primary contribution of this work lies in the design and implementation of an interoperable architecture that integrates the OGC STA and HL7 FHIR within a federated edge–cloud framework.

Accordingly, the purpose of this section is not to provide a performance or clinical evaluation, but rather to demonstrate the functional capabilities of the proposed system. A prototype implementation of the MAMAI framework is developed to illustrate the end-to-end data pipeline and its ability to support interoperable data flow.

The framework demonstrates how heterogeneous wearable data can be ingested, transformed, and represented within a standardized interoperability pipeline. The presentation layer further illustrates how wearable-derived indicators can be processed and visualized within the system. As shown in Figure 3, the framework enables the representation of time-series trends of key well-being indicators, including sleep patterns, physical activity, and stress-related signals derived from wearable data.

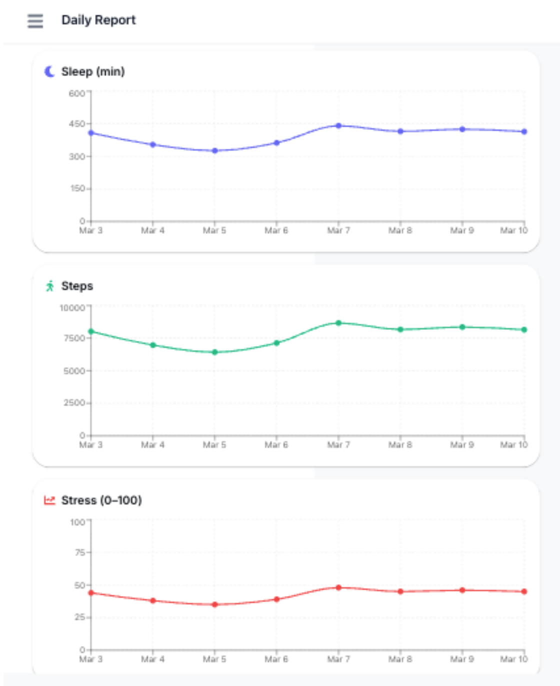
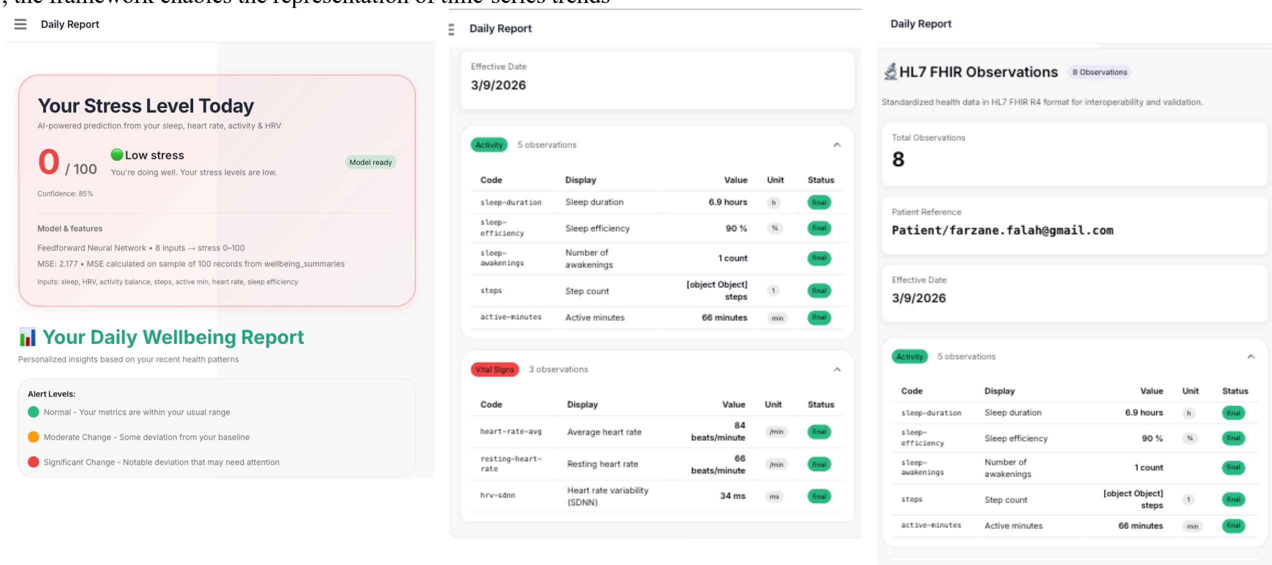


Figure 3: Trends in wearable-based well-being indicators: sleep, steps, and stress.

In addition to individual indicators, the system generates aggregated well-being insights. Figures 4 illustrate the dashboard presenting the composite well-being score, integrating sleep, activity, and HRV-based indicators.



(a) (b) (c)

Figure 4: Screenshot of the emulated MAMAI application: a) Well-being monitoring dashboard summarizing; b) overview of individual well-being indicators derived from sleep, activity, and heart-related signals. c) data and aggregated composite score with a detailed breakdown of contributing metrics.

At the interoperability level, the system ensures standardized data transformation across platforms. The OGC STA layer instantiates core IoT entities, including Things, Sensors, ObservedProperties, and Datastreams, while the HL7 FHIR transformation layer maps the processed indicators into clinically compatible representations. This interoperability mapping is illustrated in Figure 2, demonstrating the alignment between IoT sensing data and clinical data models. The operational capabilities of the proposed architecture are demonstrated through an end-to-end implementation of the system. A synthetic dataset is used to enable controlled verification of the complete data pipeline, including data ingestion, standardization, interoperability mapping, and visualization of wearable-derived indicators.

The results indicate that the proposed framework effectively integrates federated wearable data access with standardized interoperability mechanisms based on the OGC STA and HL7 FHIR. The system functions as a cohesive pipeline, supporting the transformation of heterogeneous sensor data into clinically interpretable formats and enabling user-facing well-being insights.

Overall, the implementation demonstrates the feasibility and practical applicability of the proposed architecture as a foundation for interoperable maternal digital health systems.

5. Conclusion and Future Directions

This research presents MAMAI, an interoperable and federated access for postpartum well-being monitoring that integrates open IoT and healthcare interoperability standards, specifically the OGC STA and HL7 FHIR. The proposed architecture enables seamless integration of multi-vendor wearable devices with clinical information systems through a standardized and vendor-agnostic data pipeline. By adopting a federated edge-first design, the system minimizes centralized storage of raw physiological data, thereby enhancing privacy, user control, and transparency in maternal health monitoring.

A prototype implementation demonstrates the operational feasibility of the proposed architecture, including end-to-end data ingestion, standardization, interoperability mapping, and visualization of wearable-derived well-being indicators. This proof of concept validates the feasibility of integrating heterogeneous wearable data, converting it into clinically interpretable representations, and delivering it via a unified monitoring interface to support continuous and scalable postpartum well-being assessment.

Future work will extend the proposed framework in several important directions, including the investigation of machine learning techniques to enhance the well-being scoring mechanism by enabling the system to learn personalized recovery patterns from wearable data and improve assessment accuracy beyond rule-based approaches. A key direction involves the integration of intelligent agents and large language models (LLMs) to provide context-aware and personalized support, incorporating user-specific factors such as location, language preferences, and access to local support groups to enable more adaptive postpartum care. In addition, future work will focus on formalizing the data validation pipeline by defining concrete mechanisms for handling data quality issues, including thresholds for missing data, signal quality assessment, artifact filtering, and detection of duplicate or inconsistent records to ensure the reliability of computed indicators. Finally, longitudinal deployments and real-world evaluations will be considered to assess system performance, usability, and user adoption in practical settings.

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