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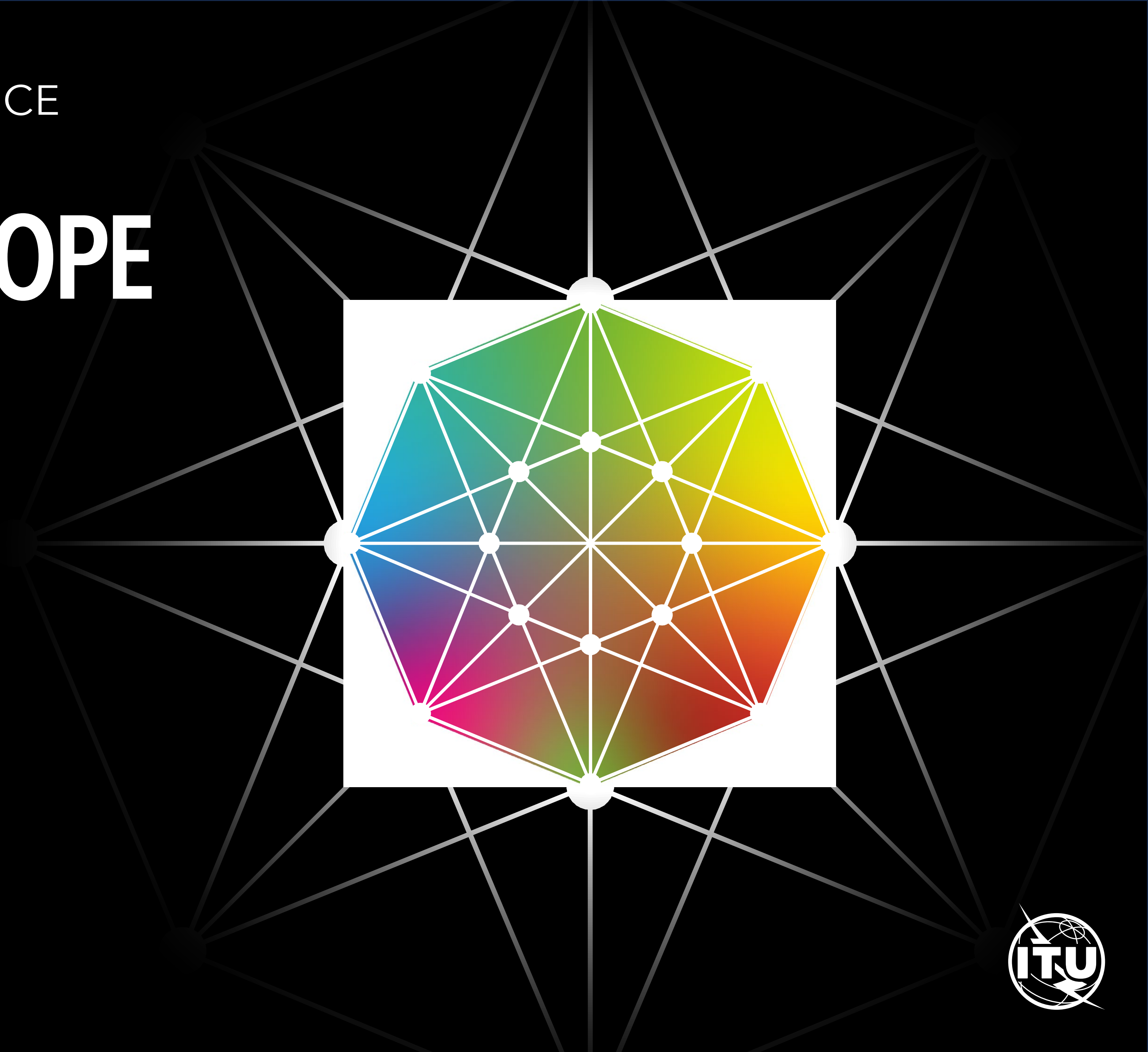

Multi-Modal Health State Monitoring System Using Wearable Sensor and Spatio-Temporal Graph Attention

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Session #S3.2

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Presentation Outline

- Motivation for continuous and real-time health monitoring
- Proposed Multi-Modal Health State Monitoring (**MHMS)** System
  - MHMS system architecture
  - Workflow of the system
  - Implementation details
    - Sensing & edge components
    - Cloud models
  - Performance evaluation
- Conclusion and recommendation

Motivation

- As per WHO 2026 report*, Non-communicable diseases cause **74%** of global deaths, but early warning signs like chronic stress and poor sleep go unnoticed.
- Current health platforms are siloed, creating fragmented data that lacks interoperability and timeline modeling.
- Consumer wearables offer reasonably accurate, underutilized data perfect for continuous, proactive home monitoring.

*https://www.who.int/health-topics/noncommunicable-diseases#tab=tab_1

Overview of proposed MHMS

Instead of treating vital signs as isolated metrics, MHMS maps data to **five insightful trackers**:

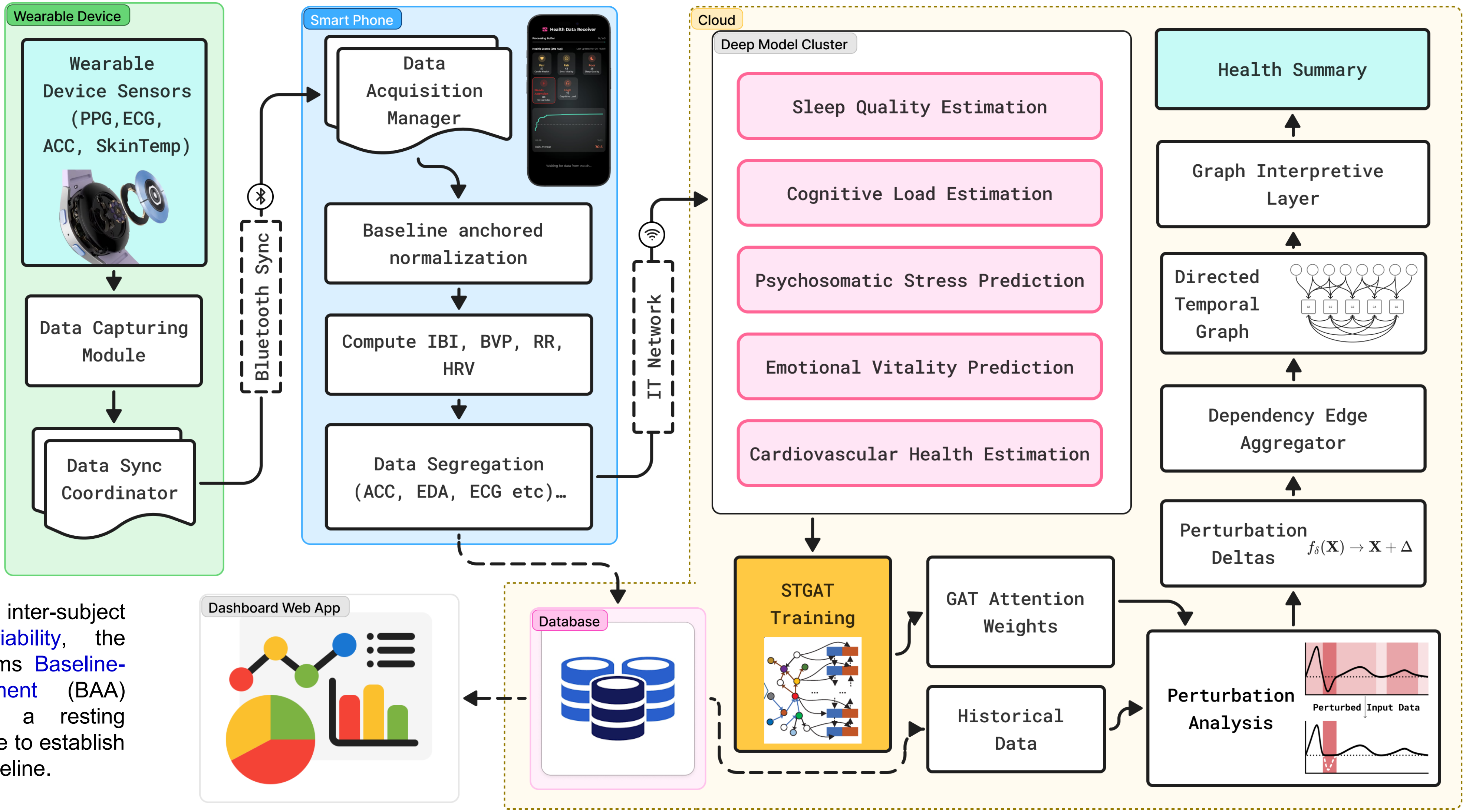
1. Sleep Quality Index **(SQI)**
2. Psychosomatic Stress Index **(PSI)**
3. Cardiovascular Health Score **(CVHS)**
4. Cognitive Load Score **(CLS)**
5. Emotional Vitality Score **(EVS)**

Spatio-Temporal Modeling: Feeds these parameters as interconnected nodes into a **Spatio-Temporal Graph Attention Transformer (ST-GAT)** to forecast health trajectories and learn temporal interdependencies.

MHMS Architecture

Photoplethysmography (PPG) is used to detect blood volume changes in the microvascular bed of tissue.

The tri-axial accelerometer helps to distinguish purposeful movement from micro-vibrations.



The data ingestion module first routes the incoming segregated batches containing aligned PPG, ACC, skin temperature and derived metrics like IBI and BVP into a **deep model cluster**.

Controlled perturbation deltas were injected into individual graph nodes while keeping the remaining node trajectories unchanged.

To address inter-subject physiological variability, the edge layer performs Baseline-Anchored Alignment (BAA) phase, capturing a resting physiological profile to establish a personalized baseline.

In ST-GAT, future state forecasting for those five parameters is utilized as a pretext training strategy to learn the inherent structural relationships between physiological states.

IBI: Inter-Beat Intervals
BVP: Blood Volume Pulse
RR: Respiration Rate
HRV: Heart Rate Variability

ACC: Accelerometer
EDA: Electrodermal Activity
ECG: Electrocardiogram

Workflow of the System

Hierarchical Three-Layer Topology (Compliant with ITU-T H.810) :

1. **Wearable Sensing Layer**:
Low-power data acquisition using consumer hardware

2. **Smart Phone Edge Layer**:
Local aggregation, preprocessing, and subject-specific baseline calibration

3. **Cloud Intelligence Layer**:
Heavy computational offloading for deep model clustering, trajectory forecasting, and perturbation analysis

Implementation Details
(Sensing & Edge layers)

Wearable (Sensing layer: Data Collection)

Device: Samsung Galaxy Watch 6

Engine: Native Wear OS 5 (Kotlin)

Role: Real-time sensor data retrieval, batching, and data transfer via Bluetooth interface

Mobile Smart Phone (Edge layer: Computing)

Engine: Android 16 (API level 36) - Kotlin running as a constant background service

Features: Live UI (Jetpack Compose Material 3) for data monitoring and immediate edge feature derivation

Core Logic: Implements baseline alignment and opportunistic sampling to compute resting baselines

IDE: Android Studio (Ladybug/Quail)

Implementation (Cloud layer: Models)

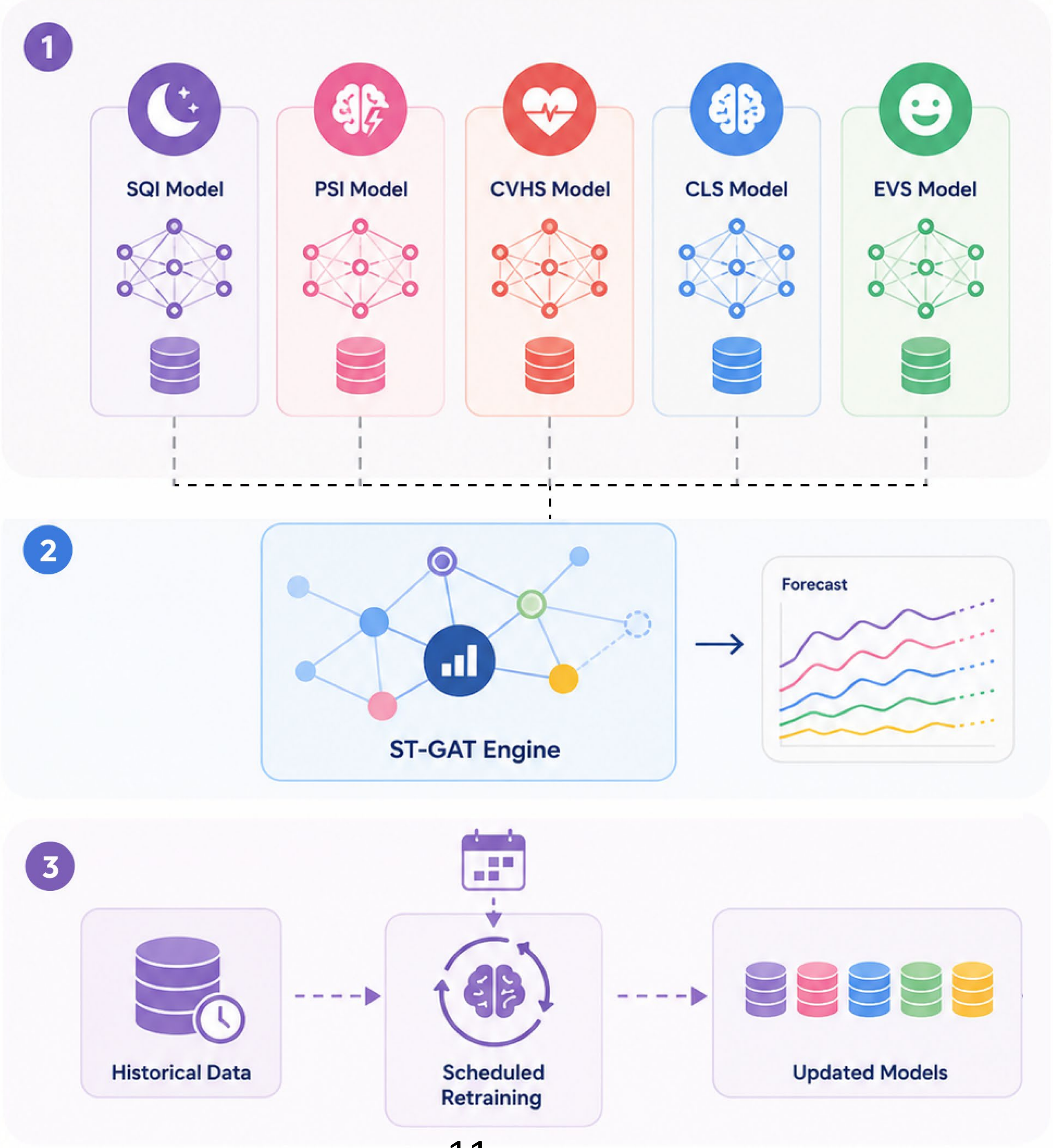
Parallel cloud inference pipeline routes incoming feature vectors simultaneously to **five specialized deep learning models**.

Each model is trained on **domain-specific datasets** to compute distinct health scores. (e.g., **DREAMT → Sleep Score**, **WESAD → Stress & Emotional Vitality**).

Models are deployed as ***Serverless Firebase Functions (Gen 2)***, automatically triggered when new derived metrics are stored. ST-GAT is triggered upon anomaly detection.

Predicted health metrics are aggregated and fed into a **ST-GAT** for **forecasting, trend analysis, and longitudinal health modeling**.

Technology Stack: TensorFlow 2.15+, Keras 3.0+, Python 3.11, Firebase Cloud Functions (Gen 2).



Performance of the System Model

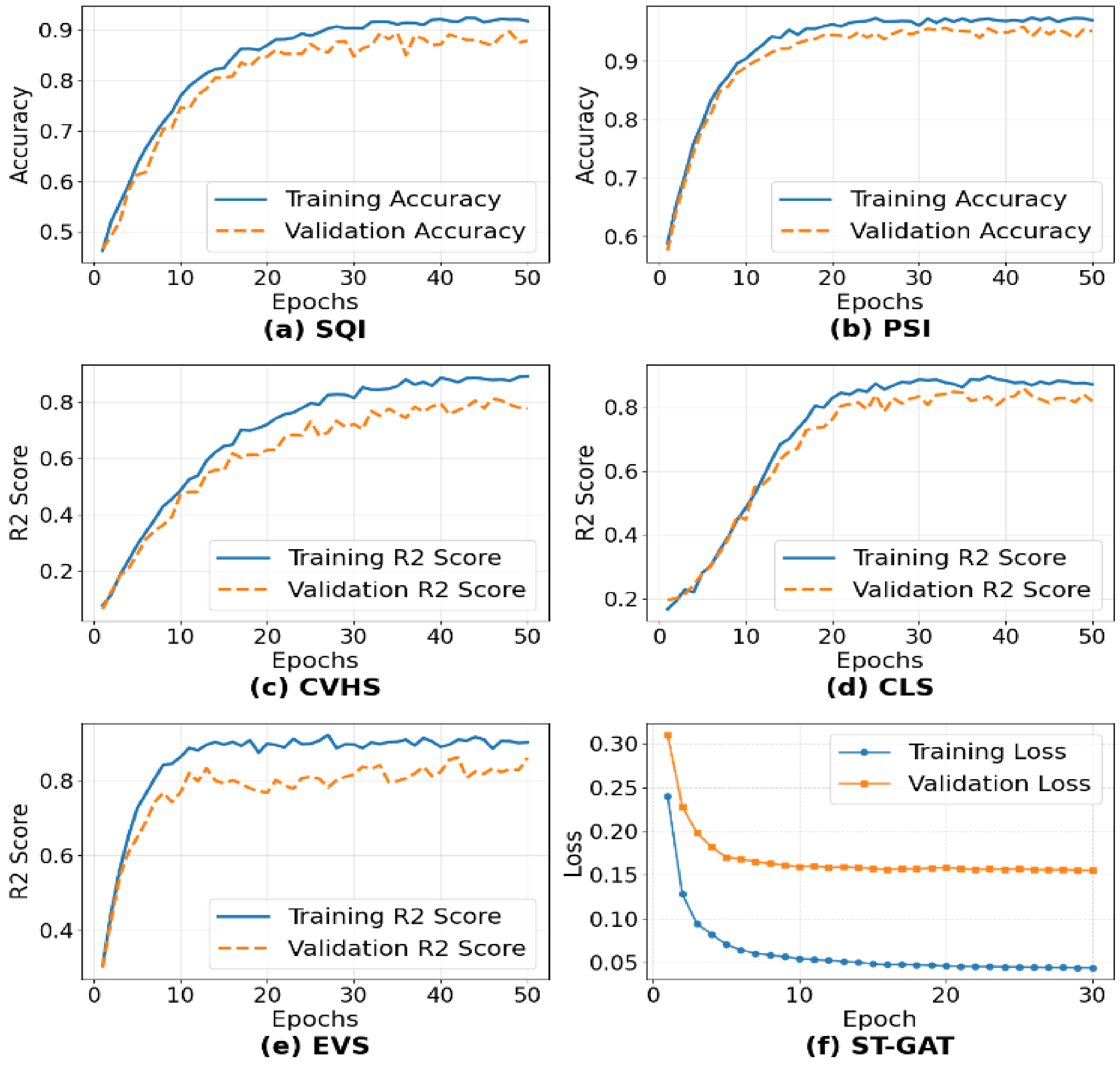


Fig 1: Performance for the health state models: (a) SQI, (b) PSI, (c) CVHS, (d) CLS, (e) EVS, (f) ST-GAT

Model / Parameter	Primary Performance
Sleep Quality Index (SQI)	88.00% Accuracy
Psychosomatic Stress Index (PSI)	95.26% Accuracy
Cardiovascular Health Score (CVHS)	R^2 = 0.81
Cognitive Load Score (CLS)	R^2 = 0.73
Emotional Vitality Score (EVS)	R^2= 0.823
Trajectory Forecasting (ST-GAT)	R^2= 0.82 (Global)

Conclusion and Recommendation

Conclusion:

- Proposed a deep learning-based Multi-Modal Health State Monitoring System
- Implemented on a consumer-grade wearables, paired with smartphone edge nodes and a cloud intelligence platform.
- Achieved classification accuracies of 88.00% and 95.26% for sleep and stress, respectively.

Standardization Perspective:

- The proposed architecture complies with the ITU-T H.810 reference model.
- It relates to ITU-T Study Group 21 work, dealing with digital health technologies.

Thank you!