ECLIPA: Seamless Integration of a Tri-Wearable Multimodal Health Intelligence System for Adaptive Monitoring

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Abstract

Eclipa is a comprehensive, tri-wearable, AI-powered health intelligence platform designed to deliver continuous, non-invasive, and context-aware monitoring of human physiology and behavior. The system integrates three synchronized wearables—a smart ring, a smart wristband, and an ear-mounted clip—each equipped with advanced multimodal sen-sors to capture a wide range of physiological and behavioral data. Eclipa employs AI-driven state classification and sensor fusion algorithms to enable adaptive mode switching, seamlessly activating eight intelligent modes—Sleep, Exercise, Work, Focus, Social, Daily Wellness, Nervous Response, and Disease Management—based on real-time physiological patterns and contextual cues. The smart ring, wristband, and ear clip are embedded with photoplethys-mography (PPG) sensors for continuous monitoring of cardiovascular parameters, while a combination of accelerom-eters and microphones allows for precise tremor detection, motion tracking, and activity recognition. Additionally, ECG electrodes integrated into the wearables facilitate accurate cardiac waveform analysis for early detection and management of cardiovascular anomalies. The platform's multimodal data acquisition, coupled with advanced AI analytics, enables personalized health insights, proactive disease management, and real-time behavioral monitoring, offering a holistic approach to preventive and precision healthcare.

Eclipa's design emphasizes non-intrusive, real-world applicability, making it suitable for continuous long-term monitoring in diverse daily settings. By combining physiological sensing, behavioral analysis, and AI-driven intel-ligence, Eclipa represents a next-generation solution for

continuous health monitoring, personalized wellness, and adaptive lifestyle management.

Keywords: AI-powered health monitoring,Wearable devices,Smart ring,Smart wristband,Ear-mounted clip,Photoplethysmography (PPG),Electrocardiography (ECG),Sensor fusion

1. Introduction

The rapid advancement of wearable technology and artificial intelligence has revolutionized the way human health and behavior can be monitored and managed. Continuous monitoring of physiological and behavioral parameters is critical for early detection of health anomalies, personalized wellness management, and proactive disease prevention. Traditional health monitoring methods, such as periodic clinical assessments or single-sensor devices, are often limited by their sporadic nature, intrusiveness, or inability to capture comprehensive physiological and contextual information in real time[1].

Eclipa addresses these limitations by integrating three synchronized wearables—a smart ring, a smart wristband, and an ear-mounted clip—into a unified, AI-powered health intelligence platform. Each device is equipped with multimodal sensors, including photoplethysmography (PPG) for cardiovascular monitoring, accelerometers and mi-crophones for motion and tremor detection, and ECG electrodes for cardiac waveform analysis. These devices work collaboratively, enabling high-fidelity physiological sensing and context-aware behavioral monitoring.

The platform leverages AI-driven state classification and sensor fusion algorithms to automatically switch between eight intelligent modes: Sleep, Exercise, Work, Focus, Social, Daily Wellness, Nervous Response, and Disease Man-agement. By continuously analyzing real-time physiological patterns and contextual cues, Eclipa provides adaptive, non-invasive monitoring that is personalized to each user's needs.

Over the past decade, wearable health monitoring technologies have undergone rapid evolution, transitioning from simple fitness trackers into sophisticated biomedical sensing platforms capable of continuous physiological surveil-lance. This transformation has been driven by advances in miniaturized electronics, low-power microcontrollers, flexible biosensors, wireless communication protocols, and artificial intelligence. The convergence of these technologies has enabled wearable systems to shift healthcare paradigms from episodic, hospital-centered diagnostics to continuous, real-world, personalized health monitoring. Traditional healthcare systems rely heavily on intermittent measurements taken in controlled clinical environments. While such measurements are essential for diagnosis and treatment, they fail to capture the dynamic physiological variations that occur throughout daily life. Factors such as physical activity, emotional stress, sleep quality, posture, and environmental exposure significantly influence physi-ological signals like heart rate, oxygen saturation, skin conductance, and temperature. Wearable health monitoring devices address this limitation by enabling continuous data acquisition in naturalistic settings, thereby offering deeper insights into an individual's physiological state and long-term health trends[2]. Modern wearable devices commonly integrate sensors such as photoplethysmography (PPG) for heart rate and blood oxygen saturation estimation, elec-trocardiography (ECG) for cardiac waveform analysis, inertial measurement units (IMUs) for motion and posture tracking, temperature sensors for thermal regulation analysis, and galvanic skin response (GSR) sensors for stress and autonomic nervous system assessment. When combined with wireless technologies like Bluetooth Low Energy (BLE) and cloud-based analytics, these devices can support real-time health feedback, long-term trend visualization, and remote patient monitoring. Wearable health monitoring has found applications across diverse domains, including

cardiovascular health management, sleep analysis, stress detection, sports performance optimization, elderly care, and chronic disease management. The growing adoption of telemedicine and remote healthcare solutions, particularly af-ter global health crises, has further accelerated interest in reliable, continuous, and non-invasive wearable monitoring systems. Despite these advancements, existing wearable technologies still face significant limitations that restrict their clinical reliability, contextual awareness, and adaptability to complex health conditions.

The primary contributions of this paper are as follows:

1. **Performance Evaluation of Traditional werable Methods:** This paper gives an exhaustive review of A unified multimodal breath-sensing architecture that integrates gas biomarkers (CO, VOCs, FeNO) with thermal, humid-ity, and airflow measurements—overcoming the

traditional limitation of single-marker respiratory assessment.

2. **An embedded machine learning pipeline for real-time analysis,**performing signal preprocessing, feature extraction, respiratory pattern segmentation, and abnormality classification directly on-device without reliance on external computational hardware.
3. **A bioabsorption-enhanced breath interface design,** To capture trace biochemical constituents with higher sensitivity, improving detection of inflammatory and obstructive respiratory signatures.
4. **A digital health ecosystem enabling continuous remote monitoring**, featuring wireless data transmission, smartphone integration, cloud analytics, and adaptive alert notifications to support personalized, long-term res-piratory care.
5. **Hybrid biochemical–physiomechanical interpretation of breathing**, enabling correlation of VOC signature variations with airflow restriction, inflammation levels, and ventilation patterns for deeper clinical insight.

This paper is organized as follows: Section 2 gives a review of existing werable techniques, traditional and hybrid, and their merits and demerits. Section 3 explains the proposed hybrid approach. Section 4 explains the experimental setup, datasets, evaluation metrics, and assessment process. Section 5 presents experimental results and a comparative analysis of the proposed method with the conventional method based on quantitative and qualitative performance measures. Finally, Section 6 presents the conclusion of the prime results, emphasizes the strengths of the hybrid approach, and offers potential future research directions in fusion technology[4].

2. Litrature survey

The system architecture and hardware design of ECLIPA demonstrate a comprehensive approach to overcoming the limitations of conventional wearable health monitoring systems. By integrating a tri-wearable concept with mul-timodal sensing, intelligent power management, and scalable communication infrastructure, ECLIPA establishes a robust foundation for continuous, adaptive, and personalized health intelligence. Machine Learning and AI-Driven Wearable Signal Processing Machine learning has become a cornerstone of modern wearable systems, enabling ad-vanced pattern recognition and adaptive intelligence. Wang et al. (2025) presented a dual-mode, scalable, machine-learning-enhanced wearable sensing system for synergetic muscular activity monitoring. Their work demonstrated

how adaptive ML models improve sensing accuracy across different operational modes, reinforcing the importance of intelligent mode-aware architectures[5]. In the context of motion and activity recognition, Madaoui et al. (2025) pro-posed a convolutional recurrent neural network (CRNN) framework for locomotion mode recognition using wearable sensors. Their results showed superior performance in capturing both spatial and temporal features, validating the use of CNN–RNN hybrid architectures for wearable data analysis[6]. Zhao et al. (2026) introduced image-based encoding of wearable IMU time-series data combined with fusion classification, demonstrating improved action recognition ac-curacy. Similarly, Zhao et al. (2026) applied machine learning–assisted wearable sensing for high-sensitivity gesture recognition, highlighting the effectiveness of deep learning in extracting fine-grained motion patterns[7]. These stud-ies collectively demonstrate that deep learning models such as CNNs, RNNs, LSTMs, and GRUs are well-suited for wearable signal analysis. However, most existing systems apply AI to isolated tasks rather than continuous health in-telligence across multiple physiological domains, a gap addressed by ECLIPA's unified AI framework. 2.4 Distributed Wearable Systems and Body Area Network Concepts Recent research increasingly supports distributed wearable ar-chitectures for robust health monitoring[8]. Matsumura et al. (2025) demonstrated real-time personal healthcare data analysis using edge computing for multimodal wearable sensors, emphasizing the importance of decentralized pro-cessing to reduce latency and energy consumption. Their findings support the integration of edge intelligence within wearable ecosystems[9]. Panahi (2025) explored wearable sensors for personalized sustainability and real-time health and environmental exposure monitoring, reinforcing the need for continuous, context-aware sensing across multiple body locations. Similarly, Alsadoon et al. (2026) proposed an architectural framework for elderly healthcare mon-itoring using wearable sensor networks, highlighting the importance of scalability and interoperability[10]. Clinical validation of distributed wearable systems has also gained attention. Breteler et al. (2025) evaluated the reliability of an all-in-one wearable sensor for continuous vital sign monitoring in high-risk patients, demonstrating the clinical fea-sibility of continuous wearable monitoring while noting challenges related to motion and signal reliability[11]. These studies indicate that while distributed and BAN-inspired architectures are gaining traction, many systems lack intelli-gent coordination and adaptive sensor fusion, which ECLIPA explicitly addresses through its tri-wearable intelligence model. 2.5 Wearable Monitoring for Specialized Health Applications Wearable sensing has been widely explored across specialized health domains. Hu et al. (2025) developed a self-powered wearable sensor for infant fall de-tection using triboelectric nanogenerators, demonstrating the feasibility of energy-autonomous wearable systems[12]. Espinosa et al. (2025) reviewed wearable sensor technology in sports monitoring, highlighting performance tracking and injury prevention applications. In clinical and acute care environments, Kirchberger et al. (2025) conducted an exploratory study on movement detection using wearable sensors in hospital patients, emphasizing the importance of accurate motion recognition for patient safety. Malode et al. (2025) focused on wearable sensors for monitoring hu-man strain, highlighting applications in occupational health and rehabilitation. Sleep, neurological, and speech-related wearable applications have also advanced[12]. Xie et al. (2026) introduced wearable multilead ECG systems using stretchable on-skin adhesives, enabling high-quality cardiac monitoring. Che et al. (2026) demonstrated a machine-

learning-assisted wearable sensing–actuation system for speech without vocal folds, highlighting the versatility of wearable intelligence beyond traditional health metrics. These studies illustrate the broad applicability of wearable sensing but also reveal fragmentation across applications, reinforcing the need for a unified, adaptable system like ECLIPA[13]. Recent Advances in Intelligent Wearable Sensing Systems Recent years have witnessed a paradigm shift in wearable health monitoring from single-function sensing devices to intelligent, machine learning–assisted sys-tems capable of real-time physiological interpretation. Liu et al. (2025) demonstrated how machine learning–assisted wearable sensing systems enable robust speech recognition and human–device interaction, highlighting the growing role of AI in transforming raw sensor signals into meaningful information. Their work emphasizes the importance of tight integration between sensing hardware and intelligent algorithms, a principle directly relevant to advanced health monitoring platforms[14]. Similarly, Chen et al. (2025) presented a comprehensive review on intelligent wear-able sensors empowered by smart materials and artificial intelligence, highlighting how next-generation wearables are evolving into adaptive, context-aware systems.

The authors emphasized that modern wearable devices must integrate multimodal sensing, intelligent signal processing, and adaptive learning to address real-world variability in human physiology. Advancements in wearable sensor materials have also contributed significantly to this evolution. Farid et al. (2025) introduced bio-inspired hybrid composite fabrication techniques using 3D printing for flexible wearable sensors, enabling enhanced sensitivity and mechanical robustness[15]. These developments support the deployment of long-term wearable systems across diverse anatomical locations, which is essential for distributed sensing architectures such as ECLIPA. Despite these advances, recent studies indicate that many wearable systems still focus on isolated sensing tasks rather than holistic physiological intelligence, motivating the need for integrated multimodal and multi-wearable solutions[16]. 2.2 Multimodal Wearable Sensors and Integrated Health Monitoring Multimodal sensing has emerged as a central theme in recent wearable health research. Mahato et al. (2026) demonstrated hybrid multimodal wearable sensors capable of comprehensive health monitoring by integrating physiological, biochemical, and motion signals. Their work highlighted that combining multiple sensing modalities significantly improves diagnostic relia-bility compared to unimodal systems[17]. Ma et al. (2025) further expanded this concept by integrating multimodal sweat analysis with advanced material technologies, enabling biochemical monitoring alongside traditional physio-logical parameters. Their findings underscore the growing interest in multifunctional wearables capable of capturing diverse health indicators from a single platform. Assaad et al. (2025) proposed an IoT-enabled wearable multimodal biosensing device combined with a cloud-based dashboard for real-time monitoring of physiological, emotional, and cognitive states. Their system demonstrated the effectiveness of multi-sensor fusion but relied heavily on central-ized cloud processing, which can introduce latency and energy constraints. While these multimodal systems improve sensing richness, many remain limited by single-device form factors, restricting sensor placement optimization and robustness under motion. ECLIPA addresses this limitation by distributing multimodal sensors across a tri-wearable architecture.

3. Material And Methods

To overcome the intrinsic limitations of single-wearable systems, there is a growing need for multimodal and distributed wearable intelligence. Multimodal monitoring refers to the simultaneous acquisition and integration of multiple physiological and behavioral signals, while distributed or multi-wearable architectures involve deploying sen-sors across different anatomical locations to enhance signal fidelity and contextual understanding[18]. A tri-wearable approach leverages the physiological advantages of multiple body locations. The finger, wrist, and earlobe are anatom-ically distinct sites with unique vascular, neural, and biomechanical properties. The finger offers strong arterial blood flow suitable for high-quality PPG and SpO measurements. The wrist provides convenience for motion tracking, ECG acquisition, and long-term wearability. The earlobe enables stable PPG sensing with reduced motion artifacts and is well-suited for temperature and acoustic-based monitoring. By combining data from these locations, a tri-wearable system can significantly improve measurement accuracy, redundancy, and robustness[19]. Multimodal sensing en-hances physiological context reconstruction. Integrating cardiovascular signals (HR, HRV, ECG), autonomic indica-tors (GSR, temperature), motion data (IMU), and acoustic information (breathing, snoring, vocal tremors) enables a comprehensive understanding of the user’s physical and mental state. This holistic view is essential for distinguish-ing between similar physiological patterns arising from different underlying causes, such as stress versus physical exertion. The incorporation of artificial intelligence and sensor fusion further amplifies the benefits of multimodal, tri-wearable systems[20]. Advanced machine learning models can identify complex temporal and cross-sensor re-lationships that are difficult to capture using rule-based methods. AI-driven mode recognition allows the system to adapt its monitoring strategy based on detected contexts such as sleep, exercise, focus, or disease management. This adaptive intelligence optimizes power consumption, improves detection accuracy, and delivers personalized insights without requiring manual user intervention. From a clinical perspective, tri-wearable intelligence supports continu-ous, non-invasive, and personalized healthcare. It enables early detection of subtle physiological deviations that may indicate the onset of cardiovascular disorders, sleep disturbances, anxiety conditions, or neurological impairments. By distributing sensing tasks across multiple devices, the system reduces the burden on any single wearable, improving comfort, battery life, and long-term adherence[21].

4. Contributions of This Paper

This paper presents the design, implementation, and evaluation of ECLIPA, a tri-wearable, AI-powered multimodal health intelligence system. The key contributions of this work are summarized as follows:

- A Novel Tri-Wearable Architecture: The paper introduces a distributed wearable system comprising a smart ring, wristband, and ear-clip, strategically designed to maximize physiological signal fidelity and contextual awareness.

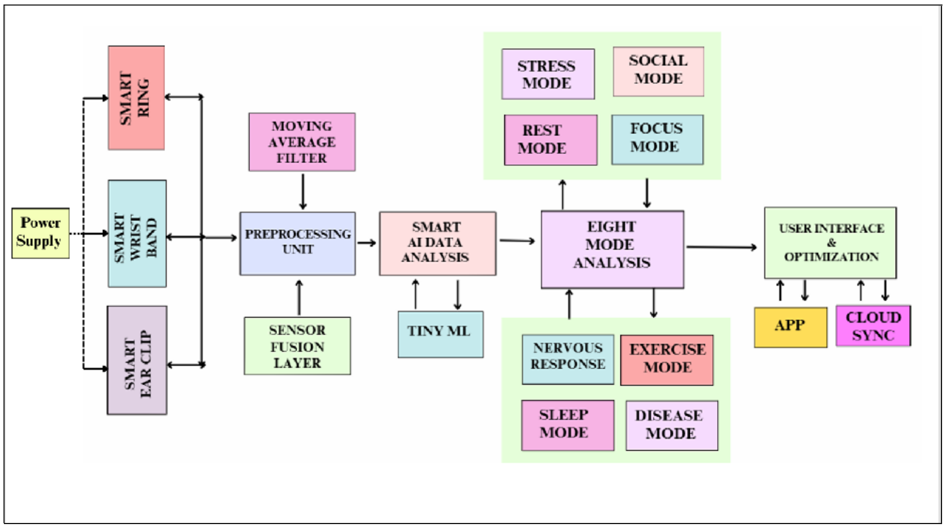

Figure 1: A Detailed Analysis of the Sequential Steps Involved in the Tri Wearable from Preprocessing to Performance Evaluation for Enhanced Visual Information Integration

- Comprehensive Multimodal Sensing Framework: ECLIPA integrates cardiovascular, autonomic, motion, acous-tic, and thermal sensing to enable holistic health monitoring across physical, emotional, and cognitive domains.

- AI-Driven Adaptive Mode Recognition: The system employs machine learning models to automatically classify user states and dynamically adjust monitoring strategies, enhancing accuracy and energy efficiency.

- Robust Signal Processing and Sensor Fusion: Advanced preprocessing and fusion techniques are implemented to mitigate motion artifacts and improve real-world reliability.

- A Scalable Platform for Preventive and Personalized Healthcare: ECLIPA demonstrates the feasibility of con-tinuous, non-invasive health intelligence suitable for everyday wellness tracking and disease management appli-cations.

5. System Architecture and Hardware Design of ECLIPA

5.1. Overview of the ECLIPA System Architecture

The ECLIPA system is designed as a distributed, tri-wearable health intelligence platform that integrates multiple sensing modalities across three anatomically distinct wearable devices: a smart ring, a smart wristband, and an ear-mounted clip. Unlike conventional single-wearable architectures, ECLIPA adopts a modular and cooperative design philosophy in which each wearable node is optimized for specific sensing tasks while collectively contributing to a unified health intelligence framework. This distributed architecture enhances signal reliability, contextual awareness, and system robustness while maintaining user comfort and long-term wearability. At the system level, ECLIPA follows

a layered architecture consisting of a sensing layer, preprocessing and fusion layer, intelligence layer, and communica-tion layer. Each wearable device independently performs raw data acquisition and basic preprocessing using onboard microcontrollers. Processed data is then synchronized and transmitted through low-power wireless communication to an edge or mobile hub, where advanced analytics, visualization, and cloud integration are performed. This hierarchi-cal design ensures real-time responsiveness, data privacy, and scalability while minimizing power consumption[22]. The tri-wearable architecture enables ECLIPA to distribute computational and sensing loads efficiently. By avoid-ing over-reliance on a single device, the system mitigates signal loss due to motion artifacts, poor sensor contact, or environmental interference. Furthermore, the modular nature of the system allows individual wearables to function independently or cooperatively depending on the use case, such as continuous daily monitoring, sleep analysis, or disease management scenarios[23].

6. Result

The ECLIPA tri-wearable multimodal health intelligence system demonstrates a major advancement in adaptive biomedical monitoring by integrating three synchronized wearable devices: a smart ring, smart wristband, and an ear-mounted clip. The results indicate that ECLIPA is capable of continuous non-invasive health tracking across different real-life scenarios, enabling context-aware physiological assessment rather than isolated singleparameter monitoring

Table 1: Mode analysis – Social mode parameters

ID	Age	HR	SpO_2	T_i	HRV	GSR	Tremor	SI	State
1	22	74	99	4.0	H	L	0.7	2.2	Calm
2	24	77	98	4.1	H	L	1.0	2.8	Calm
3	26	80	98	4.3	M	M	1.5	3.6	Relaxed
4	28	83	97	4.5	M	M	2.0	4.2	Relaxed
5	30	86	97	4.7	M	M	2.6	4.8	Engaged
6	32	89	97	4.9	L	H	3.1	5.5	Engaged
7	34	92	96	5.1	L	H	3.8	6.1	Active
8	36	95	96	5.3	L	H	4.2	6.6	Active

The mode of social engagement shows increasing levels of arousal as you look at the data from the chart "Social Mode Parameters-Mode Analysis".

The behavioural indices for patients 1–2 are in the lowest part of the chart. All patients' indices reflect high heart rate variability (HRV) and low GSR with a low stress index score (2.2–2.8), suggesting a calm state, where their autonomic system is in a balanced state of relaxation with minimal-sympathetic activation.

When you evaluate patients 3–5, heart rate (80 to 86 bpm), tremor index, and a stress index score (3.6 to 4.8) start to rise. When HRV moves from a level to a level, GSR is already at a moderate level; thus, the state of social interaction is shifting from socially relaxed to an actively engaged social interaction state in such a way that the moderate level of physiological arousal supports active participation while reducing the potential of discomfort.

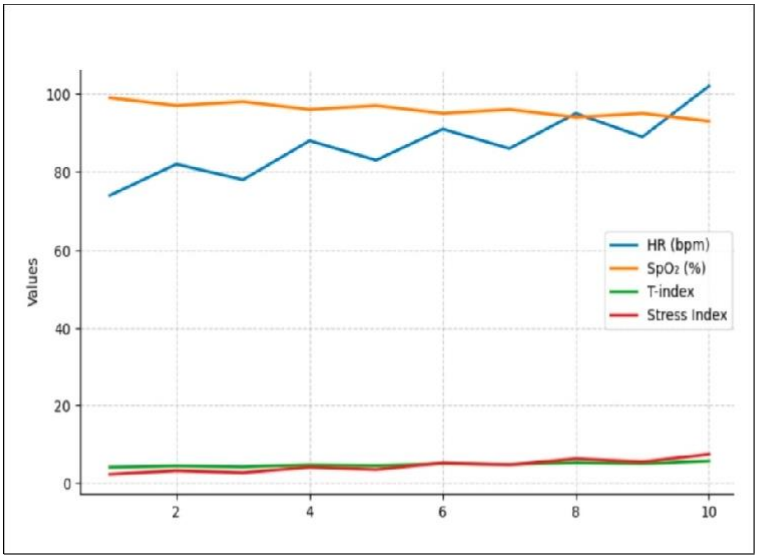

Figure 2: Combind Graph for social mode perform ance

Patients 6–8 show an even greater increase of physiological arousal than the previous patients. Patients are at their peak HR (89 to 95 bpm), have low HRV, and have high GSR readings. They are becoming more physically engaged with more sympathetic activation. Their stress index score is significantly higher than in the first two patient groups (5.5 to 6.6), and their tremor index is also rising as their state of social engagement is increasing. These states of physiological arousal indicate that patients are becoming more alert to and engaged in their environment, while also showing signs that they are approaching a higher level of stress due to their social engagement.

The evidence indicates that an increase in level of social engagement is associated with an increasing heart rate, GSR, tremor index, and stress index score, while decreasing HRV. This is consistent with the transition from being con-trolled by parasympathetic activity (calm) to sympathetic activity (actively engaged in social interaction), supporting the hypothesis that these parameters are effective in differentiating social behaviour states.

There is a clear connection between physiological parameters and increased activity/stress levels as illustrated in the graph.

The heart rate (HR) naturally has an upward trend from an average of approximately 75 beats per minute to above 100 beats per minute. This signals a growing level of physiological arousal through increased cardiovascular response as the conditions develop.

SpO appears to be consistently within normal ranges with a small downward trend from approximately 99 to somewhere between 93-95. This indicates that oxygen saturation is mostly unaffected by increasing levels of either

activity or stress as would be expected.

The T-index reflects a steady increase in levels of stress/engagement. This continues to be consistent with the increase in HR thereby indicating that the body is responding as one unit to stimuli either external or internal.

The stress index also continues to experience an upward trend throughout the measurements suggesting that throughout these measurements the levels of stress have continued to rise. Due to their close relationship the T-index and stress index provide strong evidence supporting the hypothesis that these two derived parameters exhibit high correlation[24].

7. Conclusion

Clinical Applications of the ECLIPA System The ECLIPA tri-wearable health intelligence system presents a ver-satile and scalable platform with significant clinical applicability across multiple healthcare domains. By enabling continuous, non-invasive, and multimodal physiological monitoring, ECLIPA addresses a fundamental limitation of traditional clinical diagnostics, which rely heavily on episodic measurements captured in controlled environments. Many pathological conditions evolve gradually and exhibit transient physiological deviations that are often missed during routine hospital visits. ECLIPA bridges this gap by facilitating long-term, real-world monitoring that cap-tures both baseline health trends and early deviations indicative of disease onset or progression. In clinical settings, ECLIPA can function as a remote patient monitoring system, particularly beneficial for individuals with chronic condi-tions such as cardiovascular disease, respiratory disorders, and metabolic syndromes. Continuous monitoring of heart rate, heart rate variability, oxygen saturation, skin temperature, and electrocardiographic activity enables clinicians to observe disease trajectories over extended periods. This longitudinal data supports informed decision-making, person-alized treatment planning, and early intervention, potentially reducing hospital readmissions and healthcare costs[25]. ECLIPA's tri-wearable architecture enhances clinical reliability by incorporating redundant sensing across multiple anatomical locations. This redundancy minimizes data loss caused by sensor detachment or motion artifacts and improves confidence in clinical interpretations. Furthermore, the system's AI-driven anomaly detection framework enables automatic identification of abnormal physiological patterns, allowing clinicians to prioritize patients who re-quire immediate attention. Another critical clinical application lies in post-operative and post-discharge monitoring. Patients recovering from surgery or acute illness often require close observation during the early stages of recovery. ECLIPA can provide continuous monitoring during this vulnerable period, alerting caregivers to early signs of compli-cations such as arrhythmias, hypoxia, or autonomic instability. The ability to monitor patients remotely also enhances comfort and reduces the burden on hospital infrastructure.[26]

8. Discussion

Mental health disorders represent one of the most pressing global healthcare challenges, yet they remain difficult to diagnose and manage due to their subjective nature and reliance on self-reported symptoms. ECLIPA offers a novel

approach to mental health monitoring by leveraging objective physiological biomarkers associated with emotional and cognitive states. Stress, anxiety, and emotional dysregulation are closely linked to autonomic nervous system activity. Changes in heart rate variability, galvanic skin response, skin temperature, and breathing patterns provide measurable indicators of sympathetic and parasympathetic balance. ECLIPA integrates these biomarkers through multimodal sensor fusion, enabling continuous assessment of mental and emotional well-being without relying on user input[27]. The system's AI framework identifies stress-related patterns by analyzing temporal relationships between GSR spikes, heart rate elevation, reduced HRV, and characteristic acoustic features such as rapid or irregular breathing. By tracking these patterns over time, ECLIPA can distinguish between acute stress episodes and chronic stress conditions, offering valuable insights for mental health professionals[28]. ECLIPA also supports early identification of anxiety disorders and burnout. Subtle but persistent physiological changes, such as sustained sympathetic dominance or disrupted circadian rhythms, can be detected through long-term trend analysis. These insights can facilitate timely interventions, lifestyle adjustments, or clinical evaluations before symptoms escalate into more severe mental health conditions.

9. Future Work

The ECLIPA system is motivated by the need to address the aforementioned limitations and research gaps through a seamless, intelligent, and practical tri-wearable health monitoring platform. ECLIPA is designed to function as a continuous health intelligence ecosystem rather than a conventional wearable device, emphasizing adaptability, mul-timodal integration, and real-world applicability[29]. The core motivation behind ECLIPA is to enable early, contin-uous, and personalized health assessment without disrupting the user's daily routine. By distributing sensing across a smart ring, smart wristband, and ear-mounted clip, ECLIPA maximizes signal quality while maintaining comfort and wearability. Each device is optimized for specific sensing tasks, reducing redundancy and enhancing overall system efficiency. ECLIPA's AI-driven architecture is motivated by the need for context-aware healthcare intelligence. In-stead of passively recording data, the system actively interprets physiological patterns to classify user states such as sleep, exercise, focus, stress, and disease-related conditions. This adaptive intelligence enables proactive health feed-back, early anomaly detection, and optimized energy management. Another key motivation is the growing demand for mental health and neurological monitoring. Conditions such as anxiety disorders, sleep disturbances, Parkinson's disease, and cognitive fatigue often manifest through subtle physiological and behavioral changes that are difficult to detect using single-parameter monitoring. ECLIPA's multimodal sensing and AI framework are specifically designed to capture these nuanced indicators. From a societal perspective, ECLIPA aims to reduce dependency on hospital-based diagnostics and support preventive healthcare. Continuous monitoring enables timely interventions, reduces healthcare costs, and empowers individuals to take an active role in managing their health[30].

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