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INTRODUCING A PHYSIOLOGICAL WELLNESS INDEX (PWI) FOR HEALTH AND WELL-BEING

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ABSTRACT

Background: Stress-related disorders and chronic diseases are increasing globally, highlighting the need for integrative health indices that go beyond isolated physiological signals. **Objective:** We introduce the Physiological Wellness Index (PWI), a wearable-compatible composite that integrates autonomic, respiratory, and electrodermal domains into a single interpretable score for real-time wellness monitoring. **Methods:** The PWI synthesizes heart rate variability (HRV, proxied through PRV RMSSD), respiratory rate (RR, as the operational proxy for Breathing Efficacy), and electrodermal activity (EDA) through a weighted normalization framework. Each signal is scaled per participant, with RR and EDA inverted so that higher component values consistently reflect better physiology. The index outputs a 0–100 score, mapped into three actionable categories: restful (70–100), active (40–69), and distressed (0–39). The validation was performed on the ZU-PWD ’25 dataset, comprising 28 adults, 15 months of monitoring, and over 900,000 minute-level records collected using Empatica Embrace Plus devices. **Results:** Despite heterogeneous data coverage, the PWI reliably distinguished baseline from stress days and tracked acute episodes characterized by EDA spikes, suppressed HRV, and elevated RR. The composite index classified data with greater stability and offered trajectories that were more easily interpreted compared to single-signal measures. **Conclusions:** The PWI represents a transparent, sensor-driven alternative to traditional fitness and wellbeing metrics. By addressing raw multimodal physiology with actionable states, it supports preventive healthcare, workplace and educational wellness, and clinical decision-making, marking a significant step forward on the IoMT landscape.

KEYWORDS

Physiological Measure, Heart Rate Variability, Respiratory Rate, Electrodermal Activity, Medical Wearables, Digital Health Monitoring

1. INTRODUCTION

Stress-related health conditions and chronic diseases continue to rise globally, highlighting the need for metrics/indices that capture both physiological and psychological signals. Traditional metrics such as heart rate variability (HRV), respiratory rate (RR), and electrodermal activity (EDA) provide useful data but can be unclear in real-world settings due to movement, environmental factors, and individual differences. There is still a need for a clear, wearable-friendly composite index that combines these signals into one easy-to-understand score.

The Physiological Wellness Index (PWI) addresses this problem by synthesizing three common physiological signals: (i) autonomic regulation, captured through HRV, a robust marker of sympathetic–parasympathetic balance and stress adaptability (Braboszcz & Miranda, 2023); (ii) respiratory efficiency, operationalized here using RR (breaths per minute) as a proxy for Breathing Efficacy (BrE), which conceptually reflects tidal volume and oxygen saturation dynamics (Braboszcz & Miranda, 2023); and (iii) sympathetic arousal, quantified through EDA, a sensitive indicator of emotional and physiological stress responses (Rojas, 2023). While BrE represents the adaptability of respiration more broadly, our dataset provided only RR; therefore, throughout this work, RR is treated as the measurable correlation of BrE. Sharma et al. (2025a) detail the initial development and annotation of the PWI, forming the basis for the present validation using the Zayed University Physiological Wellness Dataset 2025 (ZU-PWD ’25).

The PWI produces a 0–100 score, mapped into three clinically interpretable ranges: restful (70–100), active (40–69), and distressed (0–39). This structure allows the index not only to quantify baseline wellness but also to capture transitions between states, offering actionable insights for clinicians, wellness programs, and individuals. Its integrative design is particularly relevant on the Internet of Medical Things (IoMT) era, where consumer-friendly wearables and digital health platforms demand interpretable metrics that address raw data and decision-making (Braboszcz & Miranda, 2023; Sharma et al., 2025b).

Broader studies, such as Zhang et al. (2025) identify ongoing challenges to health professionals adopting digital health technologies, including cost, digital literacy, and concerns about mental health of the users. Such challenges highlight the importance of low-burden, transparent indices such as the PWI, which can utilize IoMT devices to deliver meaningful feedback without imposing complexity on end-users. More contextual use cases of physiological wellness monitoring, ranging from personalized care to organizational wellness programs, have been further detailed by Sharma et al. (2025b), who situate such indices within a broader value net that integrates IoMT devices, big data, machine learning, and agentic AI.

In this study, we validate the PWI using the ZU-PWD ’25: a 15-month free-living multimodal dataset comprising 28 adults and over 900,000 minute-level records captured using Empatica Embrace Plus devices. Our approach uses strict per-participant normalization, wear-time standards, and careful channel overlap to ensure valid, interpretable results without depending on imputation or large data sets. This approach establishes the PWI as a practical and ecologically sound index, effectively addressing the gap between single-signal uncertainty and meaningful wellness evaluation.

2. RELATED WORK

PWI builds on a body of research that has established the value of individual physiological signals as markers of wellness. This section reviews the previous studies on three key components, HRV, BrE, and EDA, highlighting their mechanisms, applications, and limitations when used in isolation.

2.1 Physiological Foundations of Wellness Assessment

Physiological wellness is shaped by the interplay of cardiovascular, respiratory, and autonomic systems, with several core signals serving as noninvasive indicators of health and stress regulation. Among these, HRV, BrE (In this study, only respiratory rate (RR, breaths per minute) was available, and it is treated as the operational proxy for BrE), and EDA have been most extensively studied. Each offers distinct perspectives on autonomic balance and stress response. However, when considered in isolation, these signals can be confusing and difficult to interpret, as they are influenced by many external and individual factors.

Heart Rate Variability: HRV reflects the variation in time intervals between successive heartbeats, governed by the autonomic nervous system (ANS). The high HRV is consistently associated with stress resilience, cardiovascular adaptability, and parasympathetic flexibility, whereas low HRV predicts autonomic dysfunction, morbidity, and chronic stress exposure (Shaffer & Ginsberg, 2017; Ross et al., 2016). The recent systematic reviews and meta-analyses strengthen this evidence, showing that HRV reliably improves with interventions such as slow-paced or resonance breathing and regular physical activity (Laborde et al., 2022; Sévoz-Couche & Laborde, 2022). Despite this robustness, HRV is highly sensitive to motion artifacts, circadian rhythms, and inter-individual variability (Schumann et al., 2025). These factors limit their accuracy as a standalone signal in real-world scenarios.

Breathing Efficacy: Breathing Efficacy refers to respiratory efficiency as reflected by parameters such as respiratory rate, tidal volume, and VO_2max. BrE has been shown to decline with age but is modifiable through exercise and targeted breathing interventions, such as resonance breathing, which enhance autonomic balance and stress resilience (Courtney, 2011; Mayor et al., 2023; Chaiduang, Klinsophon & Wattanapanyawech, 2024; Steffen et al., 2017). The clinical studies further highlight its relevance for conditions such as asthma, Chronic Obstructive Pulmonary Disease (COPD), and hypertension (Thomas et al., 2019; Rojas-Córdova et al., 2023). However, BrE lacks interpretive precision: for example, an increased respiratory rate could indicate stress, exertion, anxiety, or environmental factors, which makes it hard to differentiate between them when considered alone.

Electrodermal Activity: EDA is a sensitive marker of emotional arousal and stress reactivity, and it is measured as changes in skin conductance under sympathetic nervous system control. It has been widely applied in psychophysiology and affective computing, reliably detecting both acute and chronic stress responses (Posada-Quintero et al., 2020; Ghiasi et al., 2020). Its advantages include noninvasiveness and high temporal resolution. However, EDA is also highly dependent, being influenced by ambient temperature, hydration status, and sensor placement, which compromises its reliability in uncontrolled environments (Sharma et al., 2025a; Romine et al., 2022).

All three biomarkers, HRV, BrE, and EDA, provide complementary indicators of autonomic regulation, respiratory efficiency, and sympathetic arousal. Each signal contributes valuable but

partial information, and their susceptibility to confusing factors limits interpretability when applied independently. This incentive has led to the development of composite frameworks that combine these physiological domains into more robust and ecologically valid wellness indices, forming the conceptual basis for the PWI.

2.2 Interrelations and Composite Indices

While HRV, BrE, and EDA each provide valuable insights into physiological health, research increasingly shows that they are complementary rather than redundant. HRV reflects autonomic flexibility, BrE captures respiratory efficiency, and EDA indexes sympathetic arousal. When combined, these measures provide a more complete view of stress, recovery, and overall wellness than any single signal can achieve (Mayor et al., 2023; Ghiasi et al., 2020).

This has motivated the development of composite indices that integrate multiple physiological domains. Early work combining HRV and EDA showed improved accuracy in identifying stress states (Ghiasi et al., 2020), while more recent studies have used entropy and fractal measures to differentiate between breathing patterns and autonomic responses (Mayor et al., 2023; Callara et al., 2021). Such approaches highlight the value of calibration to individual baselines, which improves ecological validity and personalization in real-world monitoring (Romine et al., 2022).

The traditional indices include VO_2max, which requires clinical exertion testing, and the WHO-5 Wellbeing Index, which is based on self-reported information. The composite frameworks thus represent a necessary step toward wearable-compatible, real-time measures of wellness. Table 1 presents landmark studies that show this progression from single-signal applications to integrative approaches.

Table 1. Studies Exploring Integrative Use of HRV, BrE, and EDA

Ref.	Methodology	Sample Size	Key Results	Focus
(Laborde et al., 2022)	Systematic review & meta-analysis	223 studies	Slow and resonance breathing increases vagally mediated HRV	Breathing & HRV
(Ghiasi et al., 2020)	Experimental, signal analysis	26 healthy adults	Combined HRV & EDA indices differentiated stress states (73% accuracy)	HRV–EDA integration
(Mayor et al., 2023)	Experimental, signal processing	44 healthy adults	Fractal and entropy measures of HRV/EDA supported composite indices	Composite indices
(Callara et al., 2021)	Multivariate autoregressive modeling	30 adults	Modeled parasympathetic–sympathetic interactions using HRV & EDA	Autonomic interactions
(Posada-Quintero et al., 2019)	Reproducibility study	20 adults	HRV and EDA indices showed high reproducibility under controlled settings	Reproducibility
(Milstein & Gordon, 2020)	Device validation (E4 wristband)	30 participants	HRV measures are reliable; EDA less reliable in interactive contexts	Device reliability

2.3 Methodological Advances and Challenges

The recent advances in wearable and contactless sensing technologies have made it possible to continuously monitor HRV, BrE, and EDA in real-world conditions. The devices such as the Empatica Embrace plus, ECG/PPG sensors, and even mattress-based systems now allow the high-resolution and multimodal data capture outside of the laboratory settings (Milstein & Gordon, 2020; De Tommasi et al., 2023). These innovations mark a significant step toward scalable wellness monitoring.

Nonetheless, several methodological challenges remain. HRV and EDA signals are highly susceptible to motion artifacts, environmental confounds (e.g., temperature, humidity), and variability in sensor placement. The device reliability studies show that while HRV metrics are generally stable, EDA remains less reproducible, particularly in ambulatory or interactive contexts (Posada-Quintero et al., 2019; Milstein & Gordon, 2020). Moreover, a lack of standardized protocols makes it difficult to compare results across studies, limiting reproducibility and slowing progress toward validated clinical adoption.

Another challenge concerns interpretability. While single-signal measures such as HRV and EDA are useful, they often lack specificity, high EDA may indicate emotional stress, physical exertion, or even environmental heat. Similarly, elevated respiratory rates can reflect either metabolic demand or anxiety. The composite indices such as PWI are motivated in part by these interpretive gaps, but their reliability depends on transparent weighting frameworks and robust calibration.

Table 2 presents key claims from recent research and the strength of supporting evidence. These findings show both the promise of physiological signals for wellness monitoring and the areas where methodological advances are still needed.

Table 2. Summary of biomarkers and their evidence strength in health assessment

Claim	Evidence Strength	Reasoning	Supporting References
HRV is a robust marker of autonomic and cardiovascular health, declining with age but improving with physical activity	Strong (9/10)	Supported by large meta-analyses and systematic reviews across populations	(Laborde et al., 2022; Sévoz-Couche & Laborde, 2022)
Slow-paced and resonance breathing improve HRV and autonomic balance	Strong (8/10)	Multiple RCTs and meta-analyses confirm consistent effects	(Laborde et al., 2022; Mayor et al., 2023; Chaiduang, Klinsophon & Wattanapanyawech, 2024)
EDA is a sensitive marker for acute and chronic stress but less reliable for physical fatigue	Moderate (7/10)	Supported by experimental studies but affected by environmental and methodological confounds	(Ghiasi et al., 2020; Romine et al., 2022; Yu et al., 2024)
Composite indices (e.g., PWI) integrating HRV, BrE, and EDA enhance wellness assessment accuracy	Moderate (6/10)	Early evidence shows improved sensitivity, but validation is still limited	(Mayor et al., 2023; Ghiasi et al., 2020; Callara et al., 2021)

Device reliability and methodological confounds limit accuracy of HRV and EDA in ambulatory settings	Moderate (5/10)	Device validation and reproducibility studies highlight inconsistent results	(Posada-Quintero et al., 2019; Milstein & Gordon, 2020)
Persistently low HRV or BrE and elevated EDA may indicate underlying health concerns	Moderate (4/10)	Observational and clinical studies show associations, but causality remains unclear	(Laborde et al., 2022; Thomas et al., 2019; Anwer et al., 2020)

2.4 Research Gaps and Open Questions

There is evidence indicating that HRV, BrE, and EDA function as physiological markers; however, there are still unresolved issues. The composite indices are still under-validated across diverse populations, with most studies focusing on healthy adults in controlled environments. The chronic disease groups, ambulatory monitoring contexts, and device validation studies are currently limited in representation, which affects generalizability. Additionally, calibration protocols that account for individual baselines are not yet standardized, which is important for interpretation in real-world settings. Table 3 summarizes research strengths and gaps across major domains. Table 4 lists ongoing open questions in the field.

Table 3. Research Coverage by Topic and Study Attribute from Background Review)

Topic / Attribute	Healthy Adults	Chronic Disease	Ambulatory Monitoring	Device Validation	Composite Indices
HRV	18	7	6	5	4
BrE	12	5	3	2	3
EDA	10	3	4	2	2
Composite Indices	4	1	2	1	5
Environmental Factors	6	2	2	1	1

Table 4. Open Research Questions in Physiological Wellness Monitoring

Question	Why It Matters
How could composite indices be standardized and validated across diverse populations?	Ensures generalizability and clinical relevance.
What are best practices for calibrating indices to individual baselines in real-world settings?	Personalization is essential for meaningful interpretation.
How might we utilize medical-grade, wearable devices for reliable HRV, BrE, and EDA monitoring?	Device accuracy remains a limiting factor in free-living contexts.

While HRV, BrE, and EDA each provide partial insights into wellness, the field continues to face challenges around standardization, reproducibility, and ecological validity. A few existing approaches systematically integrate these signals into a transparent, wearable-compatible framework. The PWI directly addresses these gaps by combining autonomic, respiratory, and electrodermal measures into a single composite index, offering a robust and interpretable approach to wellness monitoring in real-world settings.

3. EMPIRICAL METHODOLOGY

PWI was developed and validated using multimodal data collected under real-world, free-living conditions. This section details the dataset foundation, preprocessing workflow, and the computational framework used to derive the composite PWI measure. It is stated at the onset that PWI scores vary by state due to factors such as age, baseline health, and chronic conditions. Weighting would be adjusted to obtain more contextual accuracy and meaning. It is also categorically stated that the PWI does not serve as a comparative measure of wellness among people but provides a relative score of how of an individual's physiological state.

3.1 Dataset and Preprocessing

The development and validation of the PWI required a dataset that was both multimodal and ecologically valid, capturing physiological and behavioral signals over extended periods of free-living monitoring. To this end, we used the Zayed University Physiological Wellness Dataset 2025" (ZU-PWD '25), a longitudinal resource collected at Zayed University (ZU) between March 2024 and May 2025 using Empatica Embrace Plus wrist-worn devices (Dhanjoo, Ghista & Sharma, 2025). This dataset offers synchronized recordings of cardiovascular, respiratory, electrodermal, thermoregulatory, activity, and sleep domains, providing the necessary foundation for constructing a composite wellness index. The following subsections describe the dataset in detail.

3.1.1 Participants and Study Protocol

A total of 28 adult participants (staff and students) were recruited from ZU's Abu Dhabi and Dubai campuses. Everyone contributed between 10 and 30+ consecutive days of continuous monitoring, with overlapping participation periods creating a 15-month observation window. The study protocol emphasized ecological validity: participants wore the devices during all daily activities, including work, commuting, leisure, and sleep, without laboratory supervision. This naturalistic approach ensured that the dataset reflected authentic physiological variability and behavioral rhythms.

The ethical approval was obtained from the ZU Institutional Review Board (ZU23_055_F), and all participants provided written informed consent. The devices rotated between groups, followed by cleaning, calibration, and integrity checks after each use. This procedure ensured both participant comfort and near-continuous device utilization throughout the study.

3.1.2 Device Configuration and Recorded Signals

The data were acquired using Empatica Embrace Plus, a research-grade wearable equipped with multiple high-resolution sensors. The raw signals and derived metrics were consolidated into a unified minute-level dataset comprising 901,440 rows and 24 variables. These variables are organized into the following domains:

- **Cardiovascular:** Heart rate (pulse_rate_bpm) and pulse-derived root mean square of successive differences (prv_rmssd_ms) as a proxy for HRV.
- **Respiratory:** Respiratory rate (respiratory_rate_brpm) derived from PPG and accelerometer dynamics.
- **Electrodermal:** Skin conductance level (eda_scl_usiemens), reflecting sympathetic nervous system activity.

- **Temperature:** Peripheral skin temperature (temperature_celsius).
- **Activity and Movement:** Tri-axial accelerometry (counts_x/y/z), vector magnitude, step counts, activity intensity, and MET.
- **Sleep and Posture:** Sleep detection stages (light, deep, awake) and lateral posture indicators.
- **Quality and Metadata:** Wear-time percentage, missing-value reasons, timestamps (UNIX and ISO), and pseudonymous participant IDs.

This multimodal structure allows simultaneous exploration of cardiovascular, respiratory, and electrodermal dynamics alongside behavioral states, making the dataset uniquely suited for wellness assessment.

3.1.3 Data Coverage, Preprocessing, and Limitations

Although there were many modalities, data coverage differed significantly across channels. Heart rate and temperature maintained relatively high completeness (~55–60%), whereas HRV (prv_rmssd_ms) and respiratory rate showed substantial missing values (~86–88%), primarily due to motion artifacts and sensitivity to signal quality. EDA achieved moderate availability (~59%). When requiring simultaneous coverage of all three core PWI signals (HRV, RR, and EDA), the effective overlap reduced to approximately 13–14% of the total minute-level dataset. To ensure data integrity, several preprocessing and quality-control measures were implemented:

- **Aggregation:** All sensor streams were aligned and down-sampled to minute-level resolution.
- **Physiological Plausibility Caps:** Implausible values (e.g., HR > 240 bpm, RR < 6 or > 40 brpm, EDA > 75 μS, temperature < 26 °C) were excluded.
- **Wear-time Filtering:** Only minutes with ≥80% wear detection was considered valid.
- **Missing Data Handling:** No imputation was applied; instead, standardized categorical labels (e.g., not worn, no signal) documented reasons for gaps.
- **Normalization:** Signals were rescaled per participant using robust quantile scaling (1st–99th percentile) to account for inter-individual variability. HRV values were oriented positively (higher = better), while respiratory rate and EDA were inverted (lower = better).

The limitations include uneven missing values across channels, demographic homogeneity (university group), and lack of contextual metadata (e.g., environmental temperature, stress events). These constraints reduce strict sample size but were explicitly managed through conservative quality gates and robust normalization.

ZU-PWD ’25 provided the three physiological signals essential for constructing the PWI, HRV, respiratory rate, and EDA, within a unified, ecologically valid framework. Its longitudinal scope enabled the selection of baseline and stress days for comparative testing, while its multimodal structure allowed cross-validation of PWI against independent behavioral markers such as MET and sleep stage. Although strict three-channel overlap limited usable coverage, this conservative approach ensured that PWI values were derived only from high-quality, simultaneously available data, thereby strengthening the validity of subsequent analyses. This dataset served as both the foundation for PWI computation and the testbed for its validation under real-world conditions.

3.2 PWI Computational Framework

PWI provides a complete measure of physiological well-being by integrating multiple key indicators. To ensure a robust assessment, the PWI is computed using a weighted formula that synthesizes these physiological metrics:

$$PWI = \frac{(w_1 \times HRV_{score} + w_2 \times BrE_{score} + w_3 \times EDA_{score})}{(w_1 + w_2 + w_3)}$$

Where w_1, w_2, and w_3 are weight coefficients assigned to HRV, BrE, and EDA, respectively. These weights coefficients are dynamically determined based on statistical analysis, clinical validation, and empirical studies to reflect their relative contributions to overall wellness (Ross et al., 2016; Courtney, 2011; Posada-Quintero et al., 2020).

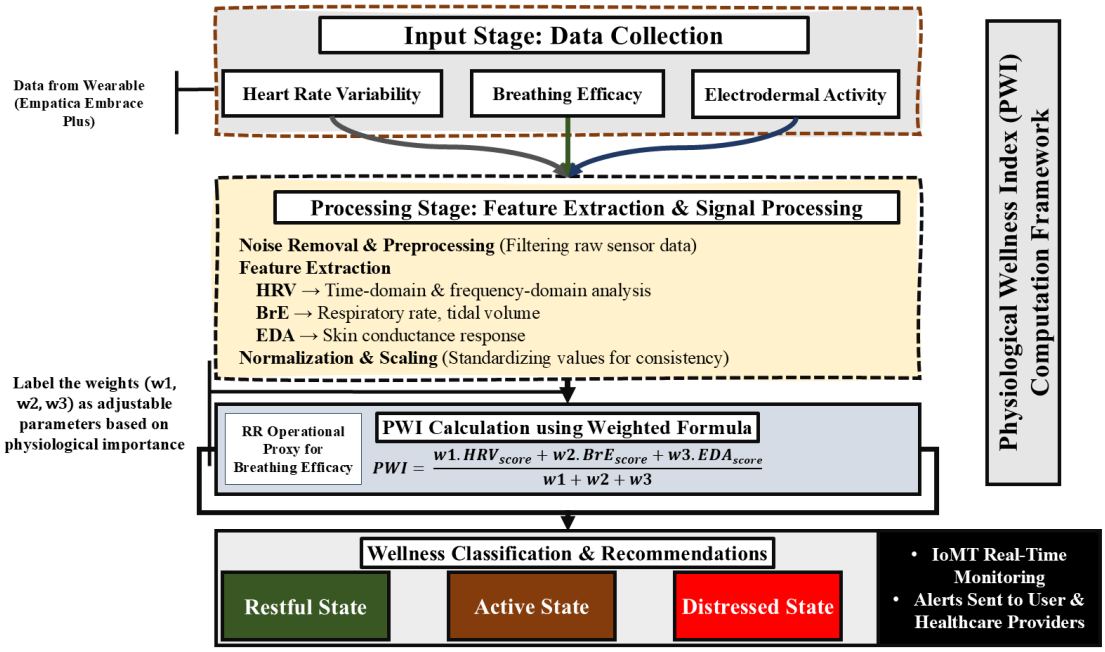

Figure 1. Computational workflow of the PWI

To illustrate the structured computational workflow of PWI, Figure 1 visually captures the transformation of raw physiological data into actionable wellness classifications. The framework consists of four primary stages:

- **Input Stage:** Data collection from wearable device, capturing HRV, BrE, and EDA signals in real-time.
- **Processing Stage:** Feature extraction and signal processing, including noise removal, normalization, and data scaling for consistency.

- **Computation Stage:** Application of the weighted formula to derive the PWI score, which dynamically adjusts based on physiological significance.
- **Output Stage:** Classification of wellness states into Restful, Active, or Distressed categories, facilitating real-time health monitoring and proactive interventions.

Such a structured approach ensures that the PWI effectively captures real-time physiological variations, enabling its application in wellness monitoring, chronic disease management, and personalized health interventions. The following section further explores how different physiological states influence PWI calculations and their practical applications.

3.2.1 Layperson Understanding of PWI Component Measures

Based on two common indicators: electrodermal activity (EDA) and heart rate variability (HRV). In particular, heart rate variability (HRV) is a measure of our body's capacity to manage stress and confront daily challenges. HRV examines the time variations of heat ate. HRV has become widely recognized as a useful way to measure recovery from endurance training, supplementing resting heart rate (RHR).

The underlying logic of the PWI is as follows. Wearable fitness devices assess our body's physiological state by analyzing data from the autonomic nervous system. This tracks wellness along the following dimensions.

Stress and recovery balance: The autonomic nervous system controls involuntary functions like our heartbeat and sweat glands. It is comprised of the sympathetic nervous system (SNS), which triggers the "flight" response, and the parasympathetic nervous system (PNS), which promotes "rest and digest".

Data from EDA and HRV: EDA primarily measures the activity of the SNS through the electrical conductance of our skin. HRV reflects the balance between our SNS and PNS. A higher, more stable HRV generally indicates better recovery, while a suppressed HRV points toward stress and fatigue.

Composite score: The PWI combines these measurements into a single score that provides an overall picture of our physiological wellness. Tracking this metric over time allows us to observe trends in our body's response to your daily activities.

Hence, the Physiological Wellness Index (PWI) is a composite of Heart Rate Variability (HRV), Breathing Efficacy (BrE), and Galvanic Skin Response (GSR). Wearables and wellness technologies combine these specific physiological metrics to provide a comprehensive wellness assessment. The process involves measuring each metric, interpreting what each indicates about the user's nervous system, and then creating a blended, weighted score that reflects their overall physiological state. Specifically:

- Heart Rate Variability (HRV)

HRV measures the subtle fluctuations in the time interval between consecutive heartbeats, controlled by the autonomic nervous system (ANS).

  - Significance: A higher, more variable HRV is a sign of a resilient nervous system and indicates that the body is in a state of rest and recovery (parasympathetic activity). A lower, less variable HRV suggests the body is under stress, fatigue, or illness (sympathetic activity).
  - Measurement: A compatible wearable device, such as a fitness tracker or chest strap, measures the timing of each heartbeat, typically during sleep or a controlled state of rest. The data is then analyzed to produce a personalized HRV score, often compared

against the user's 28-day baseline. An interesting derivation is the HRV Stabilization Score which monitors stress and then recovery.

- Breathing Efficacy (BrE)

BrE measures the quality and efficiency of a person's breathing patterns. Devices combine it with HRV to get a coherence score.

  - Significance: Coherent breathing, in which the heart rate and respiration cycle are synchronized, promotes relaxation and improved oxygen delivery. Inefficient or rapid, shallow breathing can be an indicator of stress or anxiety.
  - Measurement: This is often measured in one of three ways: i) Coherence Score: A monitor attached to an earlobe or chest calculates a heart rate coherence score, which tracks how smooth and rhythmic the heart rate is over time in sync with breathing. ii) Control Pause (CP): Users can perform a simple, home-based breath-holding test after exhaling to measure their tolerance to carbon dioxide. A longer breath-hold time indicates better breathing efficiency and less stress. iii) Breathing Sensors: Some devices use dedicated sensors to monitor the rate and depth of respiration directly.

- Galvanic Skin Response (GSR)

GSR measures the skin's electrical conductivity, which changes with sweat gland activity controlled by the ANS.

  - Significance: Emotional arousal, whether positive or negative, causes an increase in skin conductivity. This serves as an objective, unconscious measure of a user's psychological or emotional intensity. A high degree of fluctuation in GSR indicates high emotional arousal, which can be weighted negatively if it accompanies a low HRV, suggesting a stress response.
  - Measurement: Electrodes on a wearable device (typically a wristband) are placed against the skin, where they detect tiny changes in perspiration. The device sends this data to an app for analysis.

The composite PWI score is an algorithmic transformation that combines the analyzed data from each component. The raw scores are normalized to a measure of “wellness” scale from 0 to 100. Metric normalization: The individual HRV, BrE, and GSR scores are converted into a standardized format to allow for comparison. HRV is often measured against the user's personal average, while BrE and GSR are measured as changes from the individual's resting state. Algorithm weighting: A proprietary algorithm is applied to weight each metric based on its physiological importance. For example: i) Real-time monitoring: The algorithm continuously synthesizes the data to provide real-time wellness feedback. This allows the PWI to reflect a user's immediate physiological state, providing a more dynamic assessment than a single, one-off measurement. ii) Overall score: The combined scores are then synthesized into a single, comprehensive PWI score, often presented on a scale of 0 to 100. A higher score reflects a state of recovery and resilience, while a lower score indicates that the body may be experiencing stress or fatigue.

3.2.2 PWI Calculation Across Physiological States

- **Restful State**: In this state, the individual is at rest or experiencing minimal stress, with weights ranging from 1 to 14.9 to reflect physiological stability. HRV scores above 50 ms (e.g., RMSSD or LF/HF ratio) typically indicate healthy autonomic function, influenced by age and fitness level (Zhang et al., 2025). Breathing is characterized by 12–20 balanced

breaths per minute, adequate tidal volume, and oxygen saturation levels above 95% (Courtney, 2011). EDA values typically range between 0.5 and 1.5 μS, with occasional transient increases due to mild stress (Posada-Quintero et al., 2020).

- **Active State**: This state reflects moderate-to-intense physical activity, where weights range from 15 to 29.9 to capture increased energy demands. HRV typically falls below 30 ms due to heightened sympathetic activity and reduced parasympathetic tone (Zhang et al., 2025). Breathing patterns include a higher respiratory rate, reduced tidal volume, and occasionally reduced oxygen saturation, indicating inefficient oxygen delivery (Courtney, 2011). EDA values exceeding 1.5 μS signify elevated arousal and physiological stress (Posada-Quintero et al., 2020). The individual responses may vary based on physical fitness and stress tolerance.
- **Distressed State**: In this state, representing critical health crises or extreme stress, weights are elevated between 30 and 44.9. HRV becomes extremely low, indicating severe autonomic dysfunction and heightened stress (Ross et al., 2016). Breathing patterns show increased respiratory rate, reduced tidal volume, and low Peak Expiratory Flow Rate (PEFR), indicating respiratory distress (Courtney, 2011). EDA values often exceed 3.0 μS, marking extreme sympathetic arousal (Posada-Quintero et al., 2020).

The novelty of the PWI measure is its association with an article on the Yogapathy Meditation System and its Effectiveness Indices in Science. This explains the process of meditation and how it can influence the psychosomatic health state and its effectiveness indices. Without an underlying understanding of cause and effect, PWI can be just a vague quantitative study. Otherwise, the numbers do not know where they come from.

3.3 Weighting and Assessment Methodology

The PWI does not treat its three inputs, HRV, respiration, and EDA, as interchangeable. Instead, it explicitly models their relative influence on wellness across different physiological states. This weighting framework was developed to balance physiological theory, clinical evidence, and empirical behavior in the dataset. By doing so, the PWI moves beyond a simple arithmetic average and instead reflects the changing dominance of different signals as the body transitions from rest to exertion or stress.

3.3.1 Weight Derivation and Validation

The weight coefficients (w_1, w_2, and w_3) were established through a three-tiered validation pipeline:

- **Empirical Profiling of States:** Physiological data were first segmented into restful, active, and distressed intervals using the ZU-PWD ’25. Within each class, the distribution of HRV, RR, and EDA values was examined. For example, HRV was consistently higher in restful segments, while EDA rose sharply during stress-labeled intervals. These descriptive statistics provided quantitative evidence of signal shifts across states.
- **Clinical Heuristics from Literature:** Findings from previous studies were used to weigh the relative importance of each signal. For example, HRV is widely recognized as the gold-standard measure of autonomic flexibility (Zhang et al., 2025), respiration captures oxygenation efficiency (Courtney, 2011), and EDA is highly sensitive to sympathetic arousal (Posada-Quintero et al., 2020). These heuristics informed the direction and proportional scaling of weights.

- **Iterative Tuning with Time-series Validation:** Preliminary weight sets were applied to continuous daily recordings, and the resulting PWI trajectories were inspected for fidelity to expected transitions (e.g., stress events showing rapid declines, recovery periods showing gradual restoration). Through iterative adjustment, weights were fine-tuned to ensure that PWI trajectories matched both short-term dynamics (acute stress responses) and long-term profiles (baseline vs stress-day averages).

This stepwise process produced a stable and interpretable weighting scheme that is grounded in physiology and empirically validated on live, primary data.

3.3.2 State-Specific Weighting Assumptions

Although weights are derived systematically, their relative emphasis shifts depending on the physiological state:

- **Restful state:** HRV contributes most strongly, reflecting stable autonomic balance. Respiration and EDA are weighted modestly to account for normal variability without overpowering the index.
- **Active state:** The influence of RR and EDA increases, capturing sympathetic drive and elevated metabolic demand, while HRV plays a reduced role.
- **Distressed state:** RR and EDA dominate, consistent with acute stress or crisis physiology, while HRV collapses to minimal levels.

This design ensures that the PWI remains sensitive to gradual transitions (rest → active → distressed) and does not overreact to isolated fluctuations. Importantly, this approach reflects the progressive layering of stress physiology: as the system destabilizes, autonomic balance gives way to sympathetic dominance, which the weighting scheme mirrors.

3.3.3 Interpretation of PWI ranges

To translate continuous PWI values into actionable categories, scores are normalised onto three clinically meaningful ranges:

- **70–100 (Restful):** Autonomic balance, efficient respiration, and low arousal. Typical of recovery, relaxation, or stable health.
- **40–69 (Active):** Elevated physiological demand, reflecting exercise, moderate stress, or workload. Suggestions are needed for recovery or lifestyle balance.
- **0–39 (Distressed):** Severe stress or dysfunction, where sympathetic drive overwhelms regulation. May correspond to illness, burnout, or acute crises.

These ranges were chosen through a combination of clinical anchors (literature-based thresholds) and empirical modeling (distributional analyses of the dataset). These categories show how ranges function in real data and support the practical interpretability of the PWI.

3.3.4 Individual and Contextual Variability

Although the ranges above provide population-level categories, individual physiology introduces variability:

- Age and chronic conditions can reduce HRV and elevate baseline RR, shifting expected PWI values downward.
- Fitness level and VO_2max influence breathing efficiency, altering the respiration component's contribution.

- Stress reactivity varies with personality and environment, affecting EDA baselines.

The populations with advanced stress-regulation practices, such as yoga or meditation practitioners, often show lower resting heart and respiratory rates, faster recovery, and blunted stress responses. In such cases, generic thresholds may underestimate wellness, highlighting the importance of personalized calibration.

This principle also motivates adaptive models of PWI, where weights or thresholds can be individualized, and the development of complementary indices such as the Meditation Effectiveness Index (MEFI), which targets mindfulness-related adaptations.

3.4 Integration of Dataset and Methodology

ZU-PWD ’25 provided a rich but challenging testbed for developing the PWI. Several factors shaped the methodological approach:

- **Weight optimization anchored in evidence:** Instead of arbitrary “trial-and-error,” weights were systematically tuned by combining descriptive dataset statistics, clinical heuristics, and iterative validation against expected physiological transitions (rest ↔ active ↔ distressed).
- **Range stability:** Despite inter-individual variability, PWI scores consistently mapped within bounded ranges, with clear separation between wellness states. This confirmed that the weighting scheme preserved interpretability across participants and days.
- **Cross-domain consistency:** Patterns in PWI trajectories aligned with established physiological references, lower HRV and higher RR/EDA during stress, recovery-driven rebounds during rest, supporting the index’s face validity.
- **Clinical interpretability:** PWI categories remained coherent when compared to known markers of stress and resilience, such as autonomic balance, oxygenation efficiency, and sympathetic reactivity.

These factors highlight that the dataset, preprocessing strategy, and weighting methodology collectively ensured the robustness and adaptability of the PWI. Importantly, the methodological pipeline is not confined to this dataset: it can be extended to other multimodal wearable datasets, making the PWI suitable for broader wellness monitoring and clinical applications.

This closes the methodological framework and provides the foundation for the next section, where we present the empirical results and observations derived from applying PWI to baseline and stress-day comparisons, event responsiveness, and recovery dynamics.

4. RESULTS AND ANALYSIS

This section reports empirical observations from the multimodal wearable dataset using day-level visual summaries of EDA (µS), pulse/PR (BPM), and respiratory rate (brpm). For each day figure, dots denote minute-level measurements and solid lines show the smoothed trend per participant. We first summarize participant engagement to contextualize coverage, then present representative daily profiles (baseline-like vs. stress-responsive days) and multi-participant snapshots. The detailed implications and limitations are addressed in the Discussion.

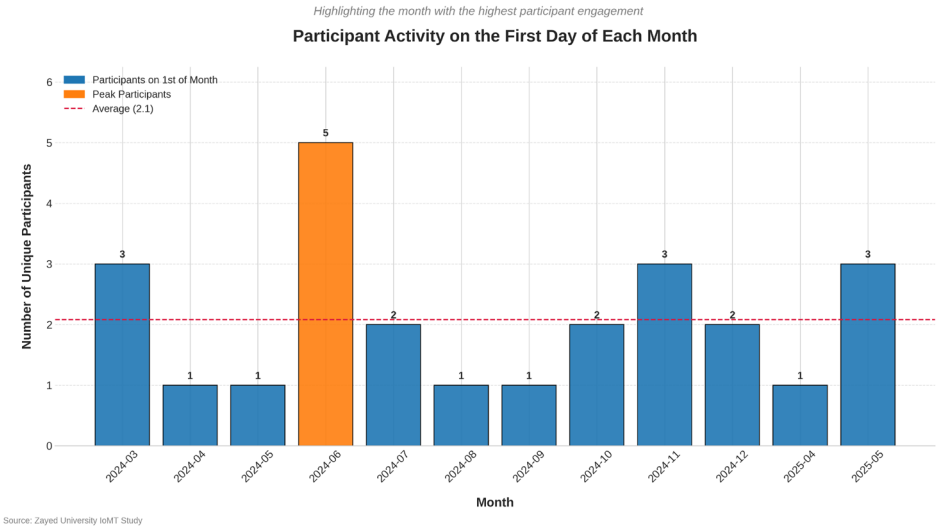

Figure 2. Participant activity on the first day of each month

4.1 Participant Engagement and Coverage

Figure 2 provides an overview of engagement on the first calendar day of each month across the observation window. The study-wide mean was ≈2.1 participants per "first-day" snapshot (dashed line). The engagement varied month to month, with June 2024 showing the highest count (5 participants). The months with three participants included March 2024, November 2024, and May 2025; months with two participants included July 2024, October 2024, and December 2024; single-participant snapshots occurred in April 2024, May 2024, August 2024, September 2024, and April 2025. This variability is useful for selecting complementary result views:

- Multi-participant days (e.g., 2024-06-01) support between-person comparisons on the same date.
- Single-participant days (e.g., 2025-04-01) provide clearer, uninterrupted within-person trends.
- Recent multi-participant days (e.g., 2025-05-01) allow examination of concurrent signal dynamics across individuals on the same timeline.

These snapshots establish the context for the day-level figures reported next (baseline-like stability vs. stress-responsive episodes) and make transparent how data richness varied across months without interpreting causes or clinical implications.

4.2 Daily Physiological Profiles: Baseline vs. Stress-Responsive Days

To show day-level signal dynamics, Figures 3 and 4 show synchronized EDA, pulse rate, and respiratory rate for contrasting scenarios.

- **April 01, 2025 (Baseline Day)**: On this day, a single participant displayed low and stable EDA values (<0.03 µS) with minimal fluctuation across the 24-hour period. The pulse rate

oscillated within a moderate range (≈70–120 BPM) and respiratory rate remained steady around 14–18 brpm. These values indicate a well-regulated physiological state, with no sharp excursions across the autonomic or respiratory channels. When processed through the PWI framework, such a pattern corresponds to the restful range, where autonomic balance and stable breathing dominate.

- **May 01, 2025 (Stress-Responsive Day)**: Three participants showed distinct EDA peaks (>10 µS), one participant exceeded 150 BPM, while others remained elevated around 100–140 BPM, and irregular breathing, indicating increased sympathetic arousal and disrupted regulation. When integrated into the PWI calculation, these deviations lower the composite score into the distressed range, reflecting the cumulative impact of sympathetic dominance and reduced autonomic recovery.

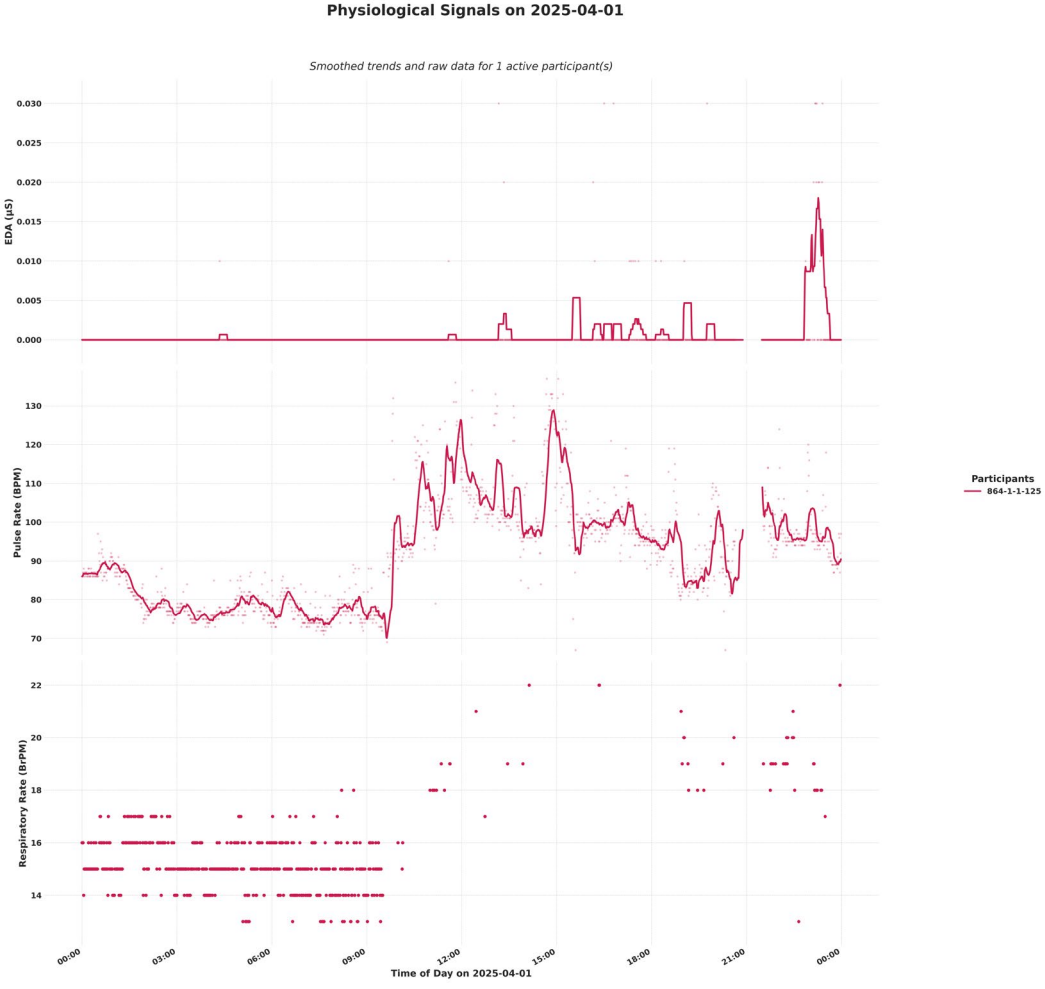

Figure 3. Physiological signals (EDA, pulse, respiratory rate) for a single participant on April 01, 2025, representing a baseline physiological state

Figure 4. Physiological signals for three participants on May 01, 2025, showing stress-responsive patterns with sharp, synchronized peaks across channels

These contrasting daily profiles show the necessity of a composite wellness measure: while individual channels fluctuate, the PWI integrates their combined trajectories to provide a single interpretable score that differentiates between restful equilibrium and distressed states.

4.3 Longitudinal variability and data quality

Beyond individual baseline and stress days, the dataset revealed substantial variability in signal availability and participant coverage across the study window. Figures 5 and 6 show these contrasts.

- **September 01, 2024 (Sparse Coverage)**: For this single-participant day, physiological signals were characterized by patchy availability. EDA remained near the noise floor (~0.03–0.04 μS) with only brief scattered values, pulse data showed discontinuous segments across the day, and respiratory rate was highly fragmented. While such sparse records lack interpretive depth on their own, they highlight the real-world constraints of free-living data collection. Within the PWI framework, this level of missing values highlights the importance of strict three-channel overlap rules and robust preprocessing to ensure composite values remain reliable.
- **June 01, 2024 (Multi-Participant Coverage)**: In comparison, this snapshot included five active participants. Here, each participant's EDA and pulse traces showed distinct but overlapping dynamics, with several participants showing parallel increases in arousal during the afternoon and evening hours. RR values were more consistently available compared to sparse days, allowing alignment across individuals. Such multi-participant days show both the heterogeneity of individual physiology and the potential for group-level synchronization. When aggregated into PWI scores, these profiles offer opportunities for between-participant comparisons and validation of consistent stress-to-recovery transitions.

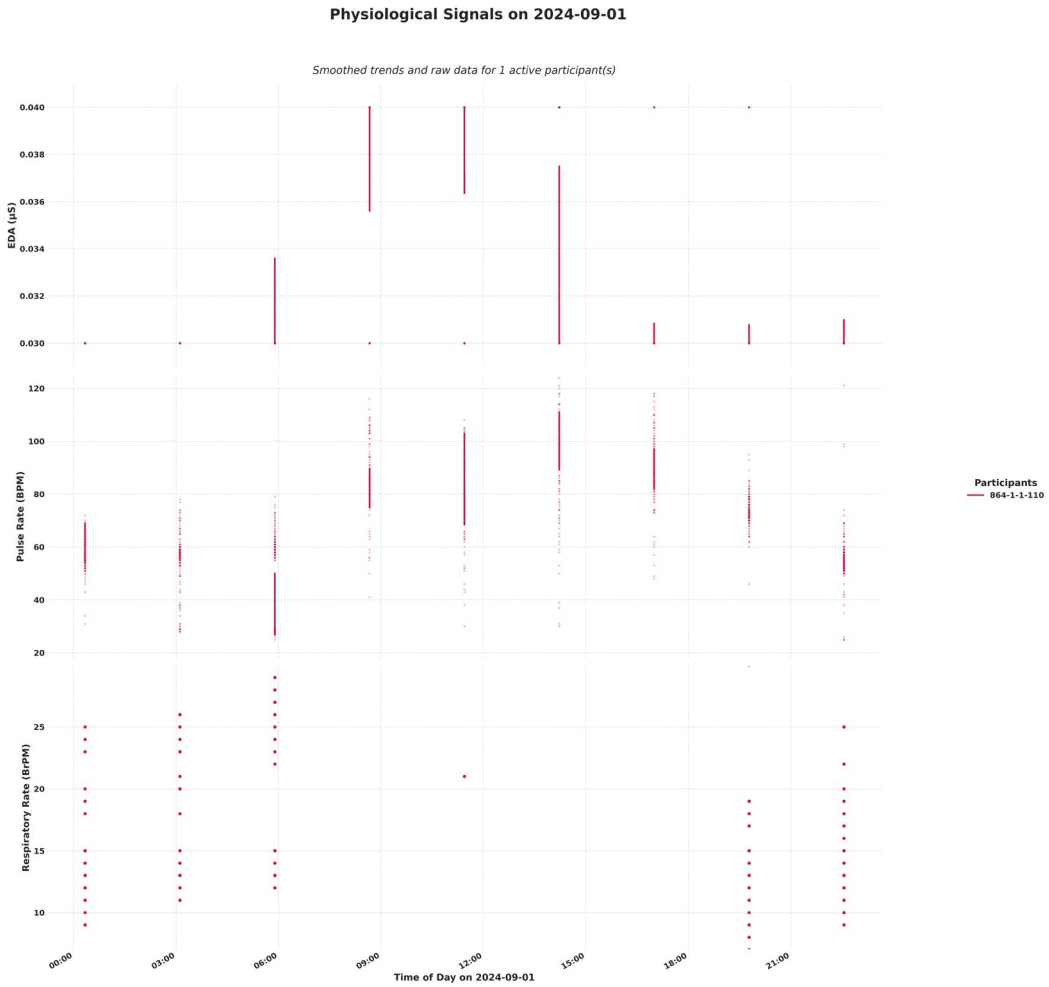

Figure 5. Physiological signals for one participant on September 01, 2024, demonstrating sparse data coverage and discontinuous signals

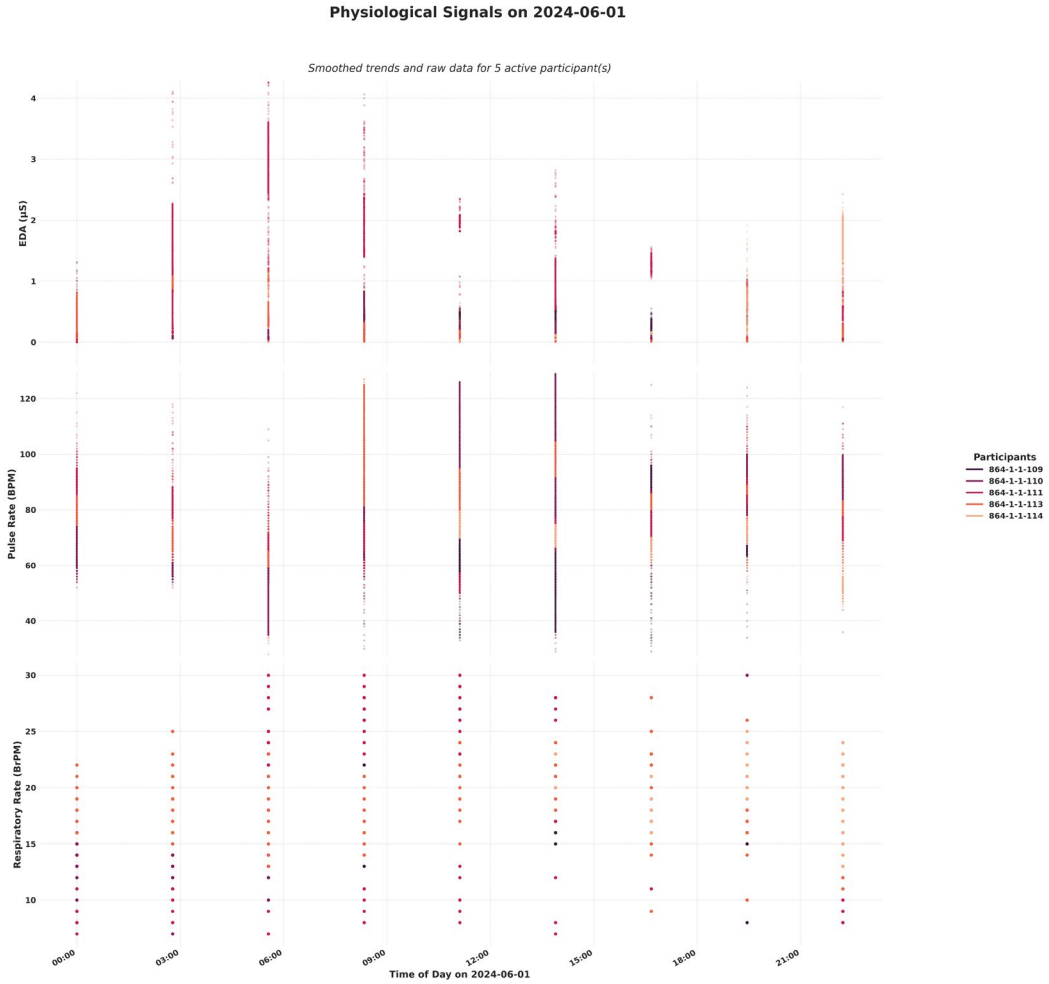

Figure 6. Physiological signals for five participants on June 01, 2024, illustrating multi-participant variability and synchronous arousal episodes

These observations support the methodological protection of the PWI. The sparse data days highlight the risk of instability if signals are used in isolation, while multi-participant records show the value of integrating HRV proxies, respiration, and EDA into a unified score that remains interpretable across individuals and conditions.

Across all representative days, a consistent tri-signal pattern was observed during stress episodes:

- EDA spikes marked heightened sympathetic activation.
- Pulse rate increases and PRV reductions reflected suppressed parasympathetic tone.
- Respiratory rate elevations indicated acute arousal and metabolic demand.

On baseline days, these signals remained stable and within narrow physiological ranges, corresponding to higher PWI values in the restful state. In comparison, stress-responsive days showed sharp deviations across channels, lowering the composite PWI into the distressed range.

The multi-participant days confirmed that while the magnitude of responses varied between individuals, the overall signal interplay followed the same trajectory, strengthening the robustness of the PWI framework.

These findings establish that PWI effectively captures the combined dynamics of autonomic balance, respiratory efficiency, and sympathetic arousal, enabling the transition from raw physiological signals to an interpretable wellness score. The following section discusses the implications of these results, their relevance for broader wellness monitoring, and directions for future work.

5. FINDINGS AND DISCUSSION

The present study introduced and empirically validated the PWI as an integrative metric that synthesizes cardiovascular, respiratory, and electrodermal signals into a single, interpretable wellness score. The results showed that while each signal provides partial insight into autonomic and stress physiology, only their combined evaluation produces a stable and actionable assessment of wellness. This section interprets the findings considering previous research studies, presents their implications, and positions the PWI as a necessary advancement over traditional single-signal metric.

5.1 Interpretation of Key Findings

The day-level analyses confirmed a consistent tri-signal pattern during stress episodes: EDA spiked, pulse rate increased with a corresponding reduction in PRV (a proxy for HRV), and RR rose above resting baselines. In comparison, baseline days showed consistently stable EDA, moderate pulse rates, and regular respiratory patterns. These patterns align with established models of autonomic stress reactivity, but by themselves, none of the signals could fully capture the distinction between restful equilibrium and distressed states.

Here, the need for PWI becomes evident. On stress-responsive days, the simultaneous integration of these signal shifts lowered the PWI into the distressed range, providing a concise and interpretable marker of autonomic imbalance. On baseline days, the same framework aggregated stable signals into the restful range, distinguishing calm regulation from moderate activation. The multi-participant records further supported this pattern: despite individual variability, the PWI consistently mapped signal interplay into meaningful ranges, ensuring interpretability across contexts.

This confirms that the PWI is not a redundant aggregation, but a necessary composite framework that:

- Reduces the ambiguity inherent in single-signal interpretations.
- Preserves sensitivity to both acute events and longer-term trends.
- Provides a standardized, wearable-compatible score that bridges raw bio signals with actionable wellness categories.

By validating this metric under free-living conditions, the findings establish PWI as a step beyond existing indices such as VO_2Max (limited to exertion-based testing) or WHO-5 (subjective self-report). The results affirm the index's potential as a real-time, multidimensional measure of stress and resilience, capable of supporting both personal monitoring and clinical applications.

5.2 Relevance and Implications

The findings position the PWI as a practical and necessary advancement for health and wellness monitoring in real-world contexts. Unlike traditional single-parameter indices, which often struggle with interpretability or ecological validity, the PWI translates multimodal physiological signals into a unified score that is both actionable and adaptable. This has several important implications:

- **Preventive Healthcare:** PWI provides a reliable, continuous measure of physiological stability, enabling early detection of stress-related dysregulation before clinical symptoms manifest. By flagging transitions into the distressed range, PWI supports timely lifestyle interventions, such as relaxation techniques or workload adjustments, that may reduce the risk of chronic cardiovascular, respiratory, or mental health conditions. In this way, PWI aligns directly with the shift toward preventive and precision healthcare.
- **Workplace and Educational Wellness:** Modern organizations increasingly recognize the cost of stress and burnout. PWI offers an objective, non-invasive tool to track wellness trends among employees or students without relying on subjective surveys. By detecting consistent stress patterns across working or learning days, PWI provides opportunities for targeted support programs, ensuring productivity while protecting well-being. In comparison to commercial readiness scores with unclear methods, PWI is transparent, based on physiology, and supported by research.
- **Clinical and Therapeutic Applications:** In clinical settings, PWI can complement existing biomarkers by providing continuous, real-time monitoring of patient physiology under everyday conditions. This is especially relevant for populations with chronic illnesses, such as cardiovascular disease, COPD, or anxiety disorders, where autonomic and respiratory regulation is central to disease management. For therapists and clinicians, the PWI enables objective tracking of treatment response, for example, stress-reduction practices such as yoga, meditation, or breathing therapy produce measurable changes in physiological resilience.
- **Positioning Relative to Existing Indices:** Current benchmarks such as VO_2Max and WHO-5 play important roles but are constrained: VO_2Max requires maximal exertion testing in clinical settings, while WHO-5 is purely subjective. Commercial HRV-based stress scores are limited by their single-signal focus. PWI directly addresses these limitations by integrating autonomic, respiratory, and electrodermal components into one score, ensuring a holistic and context-aware assessment. Its wearable compatibility further ensures usability in everyday life, from daily health tracking to structured wellness programs.

5.3 Limitations

While the results support the feasibility and promise of the PWI, several limitations must be acknowledged to ensure balanced interpretation.

- **Data Availability and Coverage**: A primary limitation was the uneven completeness of physiological signals. HRV (prv_rmssd_ms) and respiratory rate showed high missing values (~86–88%), largely due to motion artifacts and sensor sensitivity in free-living conditions. EDA had moderate coverage (~59%), but strict three-signal overlap reduced

the effective dataset to only ~13–14% of total minutes. This conservative filtering ensured data integrity but also constrained the sample size for certain analyses.

- **Group Characteristics**: The dataset was derived from university staff and students, a relatively homogeneous demographic in terms of age, occupation, and health status. While useful for proof-of-concept validation, these participants may not fully represent the physiological variability found in broader or clinical populations (e.g., elderly individuals, patients with chronic diseases). Generalization of PWI thresholds therefore requires validation in more diverse groups.
- **Validation Scope**: The study emphasized descriptive case analyses (baseline vs. stress days, sparse vs. multi-participant days) rather than large-scale inferential statistics across all participants and time points. Although the observed signal interplay was consistent and physiologically plausible, future studies should include robust statistical testing, effect size estimation, and population-level modeling to confirm generalizability.
- **Weighting Framework**: The weighting of HRV, respiration, and EDA were developed through a combination of dataset profiling, literature heuristics, and iterative tuning. While this produced stable trajectories, the approach remains partly heuristic. The automated methods (e.g., data-driven machine learning optimization) and cross-validation on larger datasets will be required to refine weights, adapt to individual variability, and minimize potential bias.
- **Contextual Data Gaps**: Environmental and contextual factors (e.g., ambient temperature, stressor events, activity logs) were not systematically recorded. These factors may affect physiological signals, especially EDA, and without them, it's harder to clarify some fluctuations. Adding contextual metadata would make PWI scores more interpretable and valid in real-world settings.

5.4 Future Directions

Building on the current findings and recognizing the above limitations, several avenues for future work are both realistic and essential:

- **Enhanced Data Quality and Coverage:** Future studies should explore improved signal acquisition protocols to address missing values, including:
  - Longer monitoring durations per participant to increase the pool of usable three-signal overlap.
  - Device configurations with higher-resolution respiratory and HRV sensors to reduce motion-related dropouts.
  - Integration of redundant wearable sensors (e.g., chest bands for respiration) to complement wrist-based measurements.
- **Diverse and Clinical Groups:** Validation must be extended beyond a university sample. Testing PWI in broader populations, including older adults, patients with cardiovascular or respiratory disorders, and individuals with high occupational stress, will help establish generalizable thresholds and strengthen clinical relevance.
- **Data-Driven Weighting and Personalization:** While the current weighting framework is physiologically grounded, future iterations should use machine learning and adaptive algorithms to dynamically adjust weights based on individual baselines, contexts, and long-term trends. This would allow personalized PWI scores, accounting for differences in age, fitness, and autonomic reactivity.

- **Contextual and Behavioral Integration:** To strengthen interpretability, future deployments should integrate contextual metadata such as activity logs, sleep quality, and environmental conditions. Combining physiological inputs with behavioral and contextual data will allow the PWI to differentiate between, for example, exercise-induced arousal and stress-induced arousal, thereby improving ecological validity.
- **Complementary Indices and Extensions:** The introduction of a MEFI provides a direction to assess specialized practices such as yoga or mindfulness, where autonomic control is advanced. Together with PWI, these indices could provide a complete set of tools for tracking daily stress and evaluating wellness interventions.
- **Clinical Deployment and Decision Support:** Ultimately, the goal is to integrate PWI into digital health platforms and decision-support systems, enabling real-time feedback for individuals and actionable alerts for clinicians. The pilot studies in preventive care and chronic disease management programs could highlight the feasibility of PWI as part of routine digital health monitoring.

The discussion highlights that the PWI is not only feasible but also a necessary advancement in wellness monitoring. By integrating HRV, respiration, and EDA into a single composite metric, PWI overcomes the limitations of single-signal measures and addresses the gap between raw wearable outputs and interpretable wellness assessment. While the current study faced challenges of missing values, limited groups, and heuristic weighting, these are natural constraints of early validation. The future research directions, including diverse groups, adaptive weighting, contextual enrichment, and clinical integration, will ensure that the PWI evolves into a robust, personalized, and scalable index.

By integrating HRV, RR, and EDA into a single composite metric, the PWI overcomes the limitations of single-signal measures and addresses the gap between raw wearable outputs and interpretable wellness scores. Despite natural constraints of early validation, future research on diverse groups, adaptive weighting, and clinical integration will ensure the PWI evolves into a robust, personalized, and scalable index.

6. CONCLUDING REMARKS

Previous studies by Ray et al. (2001), Hagins, Moore & Rundle (2007), and Lau, Yu & Woo, (2015) have introduced innovative approaches for monitoring wellness and highlight the physiological benefits of interventions such as exercise, yoga, and meditation. These practices are associated with improvements in VO_2max, cardiovascular endurance, and autonomic regulation, core components reflected in the PWI framework.

In particular, yoga and meditation have demonstrated measurable enhancements in HRV, respiratory efficiency, and stress resilience. HRV improvements signal increased parasympathetic activity and greater autonomic flexibility; enhanced breathing efficiency is marked by reduced resting respiratory rates, improved tidal volume, and stable oxygen saturation. Similarly, greater stress resilience is reflected in dampened electrodermal responses to stressors, faster recovery, and lower baseline sympathetic activation. These physiological changes collectively represent a more adaptable and resilient system, reinforcing the relevance of multi-metric indices like PWI. However, the magnitude and persistence of these benefits vary depending on factors such as individual physiology, practice intensity, and duration. As such, personalization and context-aware calibration remain essential.

While current results support the feasibility and value of the PWI model, further research is necessary to validate its use across diverse populations, health conditions, and intervention types. Future studies may also explore integration with adaptive indices, such as the proposed MEFI, to extend PWI's utility in mindfulness-oriented wellness contexts.

6.1 Contributions

The PWI integrates key physiological metrics, HRV, BrE, and EDA, to offer a comprehensive and actionable assessment of an individual's health status. Recall that the PWI is calculated using the following weighted formula:

$$PWI = \frac{(w_1 \times HRV_{score} + w_2 \times BrE_{score} + w_3 \times EDA_{score})}{(w_1 + w_2 + w_3)}$$

- **Restful State:** Reflects optimal health and balanced autonomic function.
- **Active State:** Indicates increased physiological activity or moderate stress levels.
- **Distressed State:** Highlights significant physiological distress, requiring immediate medical attention.

In scenarios where a distressed state is detected, the PWI framework could trigger automated, 24*7 alerts to designated caregivers or healthcare providers, enabling timely intervention. This integration of continuous physiological monitoring into everyday life fosters a proactive and personalized approach to health management, supporting both preventive care and informed clinical decisions.

Hence, we believe that he PWI represents a transformative metric by integrating HRV, BrE, and EDA—three critical physiological signals—into a unified, real-time wellness score. Unlike traditional single-parameter metrics, PWI captures interactions across cardiovascular, respiratory, and autonomic systems, offering a dynamic and multidimensional view of individual well-being.

VO_2Max is emerging as a popular benchmark of cardiorespiratory fitness, offering strong predictive value for mortality and cardiovascular outcomes (Ross et al., 2016; Kodama et al., 2009). However, it is limited by its focus on peak aerobic capacity and the need for controlled, lab-based testing. It does not capture real-time changes in emotional state, stress variability, or autonomic flexibility. The PWI addresses these gaps through passive, wearable-based monitoring and moment-to-moment adaptability, delivering a more comprehensive view of physiological health across everyday contexts (Sui et al., 2009; Colcombe & Kramer, 2003; Prüller-Strasser, 2025).

Other indices, such as the WHO-5 Wellbeing Index, offer validated psychological screening but rely entirely on subjective self-reporting, making them unsuitable for continuous or physiological assessment (Topp et al., 2015). Commercial wellness scores from wearables (e.g., Fitbit, 2023; Garmin, 2022) provide generalized insights based on heart rate, sleep, and activity, but often lack transparency, omit key signals like electrodermal activity and respiration, and may not offer medically actionable granularity.

In contrast, the PWI provides an interpretable, sensor-driven alternative that captures autonomic, respiratory, and emotional dimensions of stress and wellness. It adapts to individual baselines, offers real-time classifications (restful, active, distressed), and supports both

immediate feedback and long-term trend analysis. This positions PWI as complementary to existing indices, and potentially superior in enabling personalized, preventive, and precision health monitoring. A summary comparison of these metrics is provided in Table 5.

Table 5. Comparison of PWI with other wellness metrics

Metric	Focus	Limitations	Real-Time Capability	Physiological Breadth
VO_2Max	Cardiorespiratory fitness under maximal exertion	Requires clinical testing; does not reflect emotional or real-time changes	Not real-time	Limited (cardiorespiratory only)
WHO-5 Wellbeing Index	Subjective psychological well-being (questionnaire-based)	Lacks physiological data; prone to bias; not suitable for continuous monitoring	Not real-time	None (purely subjective)
Stress Index (HRV-based)	Autonomic stress estimation via HRV variability	Limited to a single system; may miss contextual stress indicators	Limited real-time	Partial (HR + sleep + activity only)
PWI (Proposed)	Integrated physiological wellness (HRV, BrE, EDA) with real-time classification	Sensor reliability dependent; broader clinical validation ongoing	Fully real-time with wearables	Comprehensive (ANS, respiration, emotional stress)

6.2 Use-Cases

Looking ahead, the PWI framework can be enhanced through dynamic weight adaptation, enabling it to reflect lifestyle patterns, contextual stressors, and circadian rhythms. Future iterations may incorporate additional data streams, such as sleep quality, physical activity, and nutrition—to enrich wellness profiling. Furthermore, integrating PWI outputs into clinical decision-support systems can facilitate early warning mechanisms and tailored health recommendations, laying the foundation for precision-guided, preventive healthcare. The current model already represents a significant step forward in the quantification of wellness. By synthesizing cardiovascular, respiratory, and electrodermal signals, the PWI bridges the gap between traditional fitness metrics like VO_2Max and real-time, sensor-driven physiological monitoring. Its multidimensional, wearable-compatible design empowers individuals and clinicians to proactively manage health in natural, everyday contexts.

To address populations with advanced autonomic control, such as yoga practitioners, we had proposed a novel manner in which PWI can be supplemented with a yoga efficacy measure (Dhanjoo, Ghista & Sharma, 2025). The Meditation Effectiveness Index (MEFI) is based on observed decreases in HR during meditation and models HR over time using a power-law decay:

$$HR_t = HR_s \times t^{-k}$$

To illustrate, let HR_f be the final value of HR at the end of meditation. We can then develop the expression:

$$MEFI = k \times \left(\frac{HR_s - HR_f}{HR_f} \right) \times 100$$

This is monotopic, in the sense that, the greater the value of k and MEFI, the more effective would have been the practice of the meditation (a form of yoga). Therefore, we could utilize a wearable device that determines MEFI for meditation practitioners to track the effectiveness of their meditation regimen. This novel approach may serve as a proxy for tracking progress to wellness.

Deriving from our prior work (Dhanjoo, Ghista & Sharma, 2025), other representative use-cases could be:

- **Yoga and Mindfulness Assessment:** PWI can quantify the physiological effects of mindfulness practices by comparing HRV, BrE, and EDA before and after sessions. Yoga practitioners, often exhibiting lower resting heart and respiratory rates, tend to recover more quickly after exertion and show attenuated responses to stress. Future research may explore how their PWI patterns differ from average individuals under stress and how MEFI correlates with their autonomic regulation.
- **Workplace Wellness Programs:** Organizations can use PWI metrics to monitor employee stress patterns and overall wellness as part of well-being initiatives. Detecting early signs of burnout enables timely, targeted interventions that support productivity and mental health.
- **Clinical Applications:** In healthcare, PWI can assist clinicians in tracking patients' physiological states, enabling data-driven interventions for chronic disease management, stress regulation, and personalized care.
- **Personal Health Monitoring:** With wearable devices, PWI enables real-time tracking of physiological status, empowering users to manage their health proactively and respond to stressors as they arise.

The possibilities for application are enormous, and the need for universal wellness is acute. This article is intended as a step in that direction.

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