

# Rapid Monitoring on Physiological Management During Outdoor Hiking using Dynamic Time Warping

Muhammad Rasyid Baihaki<sup>1</sup>, Irving Vitra Papatungan<sup>2</sup>

## Abstract

Generation Z hikers face significant physiological challenges during outdoor activities, necessitating effective self-monitoring tools. While smartwatches offer biometric feedback, the impact of user awareness on physiological regulation remains underexplored. This study investigates how real-time feedback influences exertional control during mountain hiking. A quasi-experimental between-subjects design was applied, involving eight male participants divided into "aware" and "unaware" groups based on their access to smartwatch feedback. Data were collected on Mount Andong, Central Java, using commercial wearable sensors to record heart rate, calorie expenditure, body temperature, oxygen saturation, step count, and perceived exertion. Statistical tests confirmed that real-time biometric feedback significantly enhanced physiological regulation evidenced by lower heart rate, reduced calorie burn, and decreased perceived exertion in the aware group. Dynamic Time Warping (DTW) analysis of heart rate time-series further revealed more stable pacing patterns among feedback-aware participants. These findings suggest that smartwatch-assisted awareness supports improved physiological adaptation and pacing efficiency in unstructured outdoor settings. The study underscores the need to promote conscious engagement with wearable feedback, particularly in high effort physical environments.

## Keywords:

Smartwatch, Physiological Monitoring, Self-Regulation, Wearable Sensors, Adaptive Systems

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## 1. Introduction

Generation Z, defined as individuals born between 1997 and 2012, represents a digitally native population with high exposure to technology but growing vulnerability to health risks. In Indonesia, the rising prevalence of metabolic syndrome reported at over 23% of the population alongside increased cases of diabetes and hypertension among youth has raised serious public health concerns [1], [2]. These developments point to an urgent need for lifestyle interventions that promote physical activity while supporting physiological awareness and self-regulation.

One physical activity that has gained popularity among Generation Z is hiking. This activity has transcended its traditional recreational role, becoming a form of identity expression and well-being promotion. Reports from Jakpat [3] and Strava [4] highlight a surge in participation in outdoor activities, with hiking emerging as one of the fastest growing sports worldwide. In Indonesia, visitation data from Mount Gede and Patakbanteng tourism village reflect this trend, yet many participants still lack structured monitoring of their physiological exertion. Improper pacing and overexertion common during mountain hiking have been linked to endothelial dysfunction and metabolic imbalance, posing a risk

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particularly for inexperienced hikers [5], [6].

Smartwatches have emerged as a promising wearable technology that can monitor a range of physiological indicators in real-time, including heart rate, oxygen saturation, body temperature, calorie expenditure, and heart rate training zones. A growing number of Indonesian users adopt wearable devices, primarily for health tracking [7], with projections indicating a continuous rise in smartwatch usage through 2029 [8]. However, despite their widespread availability, the strategic use of smartwatches in strenuous activities like hiking remains underdeveloped. Most users tend to use the device passively viewing data after the activity without integrating real-time feedback into behavior adaptation or exertion control [9].

Theoretical perspectives on self-regulation emphasize the importance of feedback loops in supporting behavioral control. Smartwatches, when used actively, may provide external physiological feedback that encourages bodily awareness and informed decision-making during exertion. However, the extent to which users' *awareness* of real-time data affects physiological responses and fatigue perception during real-world outdoor activity has received little attention in existing literature [10].

While the burgeoning adoption of wearable technology, particularly smartwatches, has opened new avenues for health monitoring, several critical research gaps persist, which this study endeavors to address. This research offers several significant novel contributions to the field of technology-driven health monitoring, specifically within the context of physical activity in natural outdoor environments.

Firstly, our study uniquely focuses on the physiological response dynamics among Generation Z hikers. This demographic, comprising individuals born between 1997 and 2012, represents a digitally native population [11]. Despite their pervasive access to information and technology, Generation Z faces substantial health challenges, including sedentary lifestyles and increased risks of metabolic syndrome [1], [2]. By concentrating on this specific group, our research provides tailored insights into how ubiquitous technology like smartwatches can mitigate these health risks during strenuous outdoor activities.

Secondly, a major novelty lies in our in-depth investigation into the impact of user *awareness* of real-time smartwatch feedback on physiological regulation. While many studies explore general monitoring, the specific cognitive interaction of users with their physiological data and its subsequent effect on self-regulation during physical exertion remains underexplored. This study, employing a quasi-experimental design with distinct aware and unaware groups, fills this gap by directly assessing the efficacy of real-time biometric feedback in enhancing physiological control. Thirdly, we pioneer the application of Dynamic Time Warping (DTW) for the analysis of time-series physiological data collected from smartwatches within the challenging context of mountain hiking. This methodological innovation provides a more accurate and comprehensive understanding of physiological responses.

Finally, the comprehensive collection of physiological and activity data was conducted in a real-world mountain hiking scenario on Mount Andong, Central Java. Unlike controlled laboratory settings, this approach enhances the external validity of our findings, providing practical and actionable insights into the effectiveness of smartwatch-based monitoring under genuine and dynamic environmental conditions. This holistic approach significantly contributes to the practical applicability of wearable technology in outdoor sports and health management.

## 2. Related Works

Wearable technology has gained substantial attention for its capacity to continuously monitor physiological parameters in real time. Smartwatches, as integral components of the Internet of Things (IoT) ecosystem, can capture various biometric signals including heart rate (HR), oxygen saturation (SpO<sub>2</sub>), step count, and energy expenditure, thus enabling personalized health tracking [9]. However, most validation studies on wearable sensors are conducted in laboratory settings or on treadmills, primarily involving activities like running or cycling [6], [12]. These contexts limit the generalizability of findings to dynamic and unstructured environments such as hiking trails in mountainous terrain.

To address these limitations, recent studies have explored IoT-enabled wearable health systems for deployment in real-world conditions. Nasution et al. [13] developed an oximeter-based physiological monitoring tool integrated with the Blynk platform to monitor employee health in the palm oil industry. Their findings demonstrate the utility of wearable IoT solutions in high-risk, physically demanding settings.

From a behavioral science perspective, self-regulation theory provides a valuable framework to understand the influence of wearables. According to Vohs and Baumeister [14], self-regulation involves perceiving internal physiological cues and modifying behavior based on feedback. During hiking an activity that often involves prolonged physical exertion and elevation gain real-time feedback from smartwatches can serve as an external regulator to promote safer pacing and energy management. Prior research by Navalta et al. [5] and Warren [15] has indicated that real-time biometric feedback can improve bodily awareness and facilitate more adaptive behavioral responses in outdoor exercise settings.

Despite these advancements, there remains a scarcity of studies explicitly analyzing the role of *user awareness* toward smartwatch feedback in high-variability outdoor environments. Kusuma et al. [16] conducted an experimental study involving smartwatch usage, but their analysis was restricted to brief, simulated activities under indoor conditions. Meanwhile, Bizzozero-Peroni et al. [17] highlighted that unmanaged physical exertion during hiking can increase metabolic risk, suggesting the potential value of physiological feedback.

To process physiological time-series data collected during physical activity, researchers often employ dynamic alignment techniques such as Dynamic Time Warping (DTW). DTW is capable of comparing sequences of varying lengths and identifying subtle temporal distortions between them. Varatharajan et al. [18] applied DTW to classify gait patterns for early Alzheimer's detection using wearable devices, while Nurwanto et al. [19] used DTW combined with k-Nearest Neighbor (k-NN) to identify physical exercises like push-ups and sit-ups based on data from smartwatch and smartphone sensors. These studies highlight the robustness of DTW in recognizing human physiological patterns, although its application in segment-wise heart rate analysis during real-world hiking activities remains limited.

Building upon this foundation, the present study aims to fill these gaps by evaluating the effectiveness of smartwatch-based physiological monitoring during actual mountain hiking. Through a quasi-experimental design that compares users who are aware or unaware of their real-time smartwatch feedback, this study integrates statistical and time-series analyses using DTW to explore how conscious interaction with biometric data influences physiological responses, perceived exertion, and activity regulation in uncontrolled outdoor conditions.

### 3. Proposed Method

This section describes the methodological framework employed to evaluate the effectiveness of smartwatch-based physiological monitoring during hiking. The study adopts a quasi-experimental, between-subjects design involving Generation Z participants, segmented by body mass index (BMI) classification. Data were collected using wearable sensors and analyzed through statistical testing and time-series pattern recognition. The overall process, from experimental setup to data interpretation, is structured into four subsections as follows.

#### 3.1 Participants and Devices

The target population of this study comprised individuals classified as Generation Z, defined as those born between 1997 and 2012. Participants were recruited using purposive sampling based on several inclusion criteria: (1) male, (2) aged between 18 and 25 years during the study period, (3) in self-reported healthy condition, (4) inexperienced in mountain hiking, and (5) not regular users of smartwatches. These criteria were established to minimize potential bias related to training adaptation or device familiarity.

A total of eight male participants were selected and grouped based on their body mass index (BMI) classification into four categories: underweight, ideal, overweight, and obese. Each category consisted of two individuals, ensuring physiological diversity and balanced representation.

Physiological data were collected using the Huawei Watch GT 4, a commercially available smartwatch equipped with multiple biometric sensors. The device continuously recorded real-time heart rate (HR), oxygen saturation (SpO<sub>2</sub>), body temperature, calorie expenditure, step count, and duration within heart rate training zones (extreme, anaerobic, aerobic, fat burn, and warm-up). Data were captured at 5-second intervals using the Huawei Health application synced to each smartwatch.

All participants wore the smartwatch on their non-dominant wrist throughout the hiking activity. No verbal or visual cues were provided by the researchers during the experiment to avoid influencing natural responses.

#### 3.2 Experimental Design

This study utilized a quasi-experimental between-subjects design to evaluate the influence of smartwatch feedback awareness on physiological responses during real-world hiking. This design choice was informed by practical and ethical constraints that made full random assignment unfeasible, particularly given the outdoor nature of the study and the participants' differing fitness baselines. Quasi-experimental designs are widely employed in field-based health research, especially in contexts where participant behavior or environmental factors cannot be fully controlled [20], [16].

The grouping of participants into "awareness" and "unawareness" conditions was not arbitrary but grounded in prior behavioral research on wearable devices. A recent study found that while 96.5% of smartwatch users acknowledged the health benefits of the technology, only 40.85% actively monitored or recorded their physical activity [21]. This behavioral discrepancy supports the existence of distinct user profiles those who engage with biometric feedback and those who do not which reflects varying levels of self-monitoring readiness. Consequently, participants were deliberately grouped as follows:

- Awareness group: Smartwatch screens remained visible throughout the hike. Participants were instructed to consciously monitor biometric data such as heart rate and fatigue zones.
- Unawareness group: All feedback was obstructed via opaque tape over the screen. Audible and haptic feedback was disabled to eliminate any form of feedback perception.

The hiking route was standardized for all participants: Mount Andong (via Gogik trail), segmented into three distinct phases based on terrain elevation Start to Pos 1, Pos 1 to Pos 2, and Pos 2 to Summit. These trail segments served as the basis for segment-wise physiological data comparison.

Environmental exposure was also controlled: all sessions were conducted under similar conditions (e.g., temperature, sunlight, wind speed), based on weather forecasts. Participants hiked individually, without coaching or pacing cues, to preserve ecological validity while maintaining experimental control over the feedback condition.

### 3.3 Data Acquisition and Preprocessing

Biometric data were automatically recorded at 5-second intervals throughout the hiking activity using smartwatch-based monitoring. The comprehensive set of collected variables included heart rate (HR), oxygen saturation (SpO<sub>2</sub>), body temperature, calorie expenditure, step count, and time spent in five predefined heart rate training zones. Adaptive responses such as movement speed and cumulative steps were also derived from the raw data. Subjective fatigue was quantitatively measured using the Borg Rate of Perceived Exertion (RPE) scale, administered verbally immediately after the completion of each trail segment.

To ensure optimal data quality, raw datasets underwent rigorous filtering to remove sensor noise, spurious spikes, and transient signal losses. Missing values occurring within a 10-second window were robustly interpolated using linear estimation techniques. All variables were meticulously normalized per participant to account for inherent interindividual variability and to enable valid comparative analyses. Crucially, HR data were specifically formatted into segmented time-series sequences, each corresponding to the three distinct trail phases, preparatory for Dynamic Time Warping (DTW)-based pattern analysis.

An overview of each variable, its measurement method, unit, and data type is comprehensively summarized in Table 1.

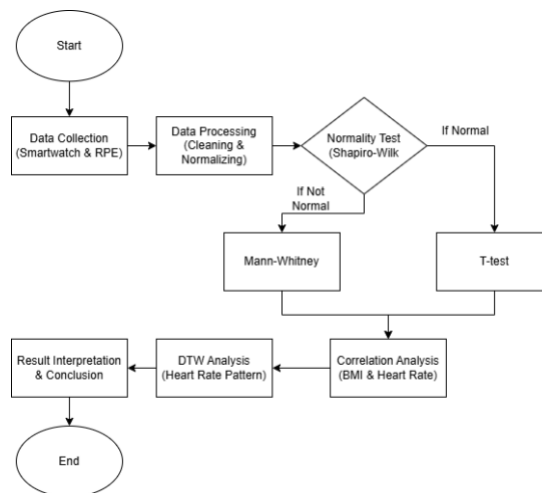
**Table 1.** Operational Definition of Research Variables

<b>Dimension</b>	<b>Variable</b>	<b>Unit</b>	<b>Measurement Tool</b>	<b>Data Type</b>
Physiological	Heart Rate	Beats per minute	Huawei Watch GT 4	Interval
	Oxygen Saturation	Percentage (%)	Huawei Watch GT 4	Interval
	Body Temperature	Degrees Celsius	Huawei Watch GT 4	Interval
	Calories Burned	Kilocalories (kcal)	Huawei Watch GT 4	Ratio
	Recovery Heart Rate	BPM(Before-After)	Huawei Watch GT 4	Derived Interval
	Heart Rate Zones Duration	Seconds	Huawei Watch GT 4	Ratio
Adaptive	Step Count	Steps	Huawei Watch GT 4	Ratio

	Movement Speed	Meters Per Second	Huawei Watch GT 4	Ratio
Perceptual	Rate of Perceived Exertion (RPE)	Score (6-20)	Borg Scale (verbal query)	Ordinal

### 3.4 Data Analysis Techniques

The analytical framework combined statistical inference, correlation analysis, and temporal pattern recognition to evaluate physiological and perceptual responses between experimental groups. The overall workflow is outlined in Figure 1.



**Fig. 1.** Analytical Workflow of the Study

Initial data analysis involved normality testing using the Shapiro-Wilk method. For variables that followed a normal distribution, independent samples t-tests were conducted. For non-normally distributed variables, the Mann Whitney U test was used. All inferential analyses were performed using a significance threshold of  $\alpha = 0.05$ .

To examine inter-variable associations, bivariate correlation analysis was employed across key physiological and behavioral metrics, including BMI, average heart rate, energy expenditure, and perceived exertion (RPE). Pearson’s correlation coefficients were calculated for normally distributed data, while Spearman’s rank-order correlations were used for non-parametric comparisons. This provided an integrative understanding of physiological interdependence between domains.

Beyond point-wise metrics, exertional patterns were assessed through time-series analysis using Dynamic Time Warping (DTW), a robust algorithm for aligning sequences that may differ in length or pacing. DTW is particularly effective in physiological contexts, where heart rate (HR) signals collected in real-world settings tend to exhibit temporal variability due to individual pacing and terrain changes.

In this study, heart rate data were segmented according to the three phases of the hiking trail: Start to Pos 1, Pos 1 to Pos 2, and Pos 2 to Summit. Each segment was normalized in length to standardize comparisons. DTW was then applied pairwise across participants to quantify the temporal similarity of their HR profiles within each phase.

Mathematically, DTW constructs a cumulative cost matrix  $D(i, j)$  between two time-series sequences  $X = (x_1, x_2, \dots, x_n)$  and  $Y = (y_1, y_2, \dots, y_m)$ , using the recurrence relation:

$$D(i, j) = (x_i - y_j)^2 + \min \begin{cases} D(i - 1, j) \\ D(i, j - 1) \\ D(i - 1, j - 1) \end{cases} \quad (1)$$

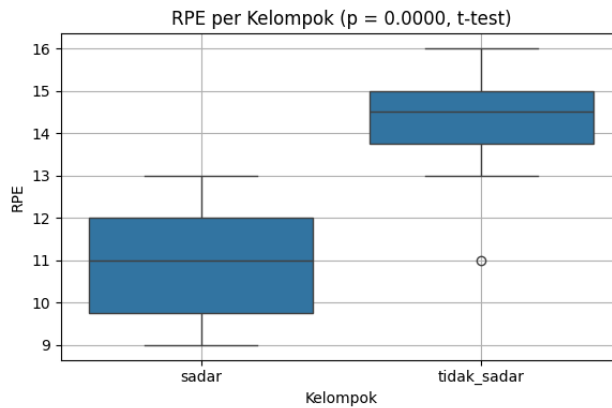
Here,  $(x_i - y_j)^2$  represents the squared Euclidean distance between two points in the sequences. The algorithm dynamically warps the sequences in time to find the optimal alignment path with the minimum cumulative cost. The final DTW distance  $D(i, j)$  reflects the degree of similarity: lower values indicate greater alignment in exertional pacing and physiological regulation between two heart rate trajectories. By leveraging DTW, this study was able to detect subtle differences in HR response patterns between participants, particularly in relation to feedback awareness. This provided a richer temporal characterization of physiological regulation than static statistical summaries alone, revealing how conscious interaction with biometric feedback may shape real-time exertional adaptation.

## 4. Result and Analysis

This section presents an integrated interpretation of the physiological, behavioral, and perceptual differences observed between the awareness and unawareness groups during hiking, based on both statistical analysis and temporal pattern recognition. Each result is interpreted in light of exertional regulation theories and real-world observations.

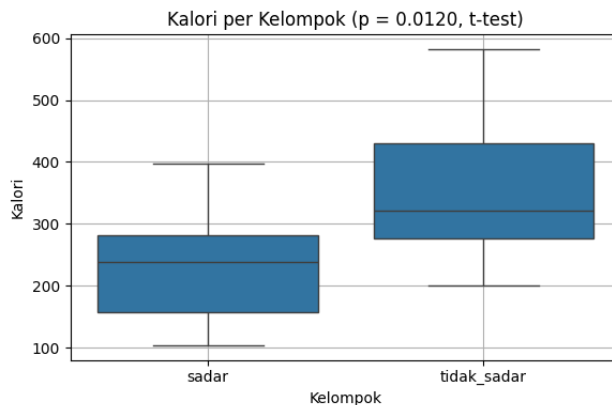
### 4.1 Comparative Analysis of Physiological Responses

The comparison of physiological indicators between the aware and unaware groups reveals compelling differences that underscore the influence of real-time smartwatch feedback on cardiovascular regulation and energy efficiency during hiking. The most prominent finding lies in the average heart rate (HR) data, where participants in the aware group exhibited significantly lower HR values compared to those in the unaware group ( $p = 0.0453$ ). This statistically significant difference suggests a more deliberate and controlled level of physical exertion among participants who could monitor their biometric information in real time. Access to such feedback appeared to facilitate self-regulation, enabling individuals to modulate their pace and effort in response to physiological cues an interpretation supported by field observations that documented more consistent pacing and fewer rest interruptions in the aware group. This distinction is illustrated in Figure 2, which presents the boxplot comparison of average heart rate between groups.



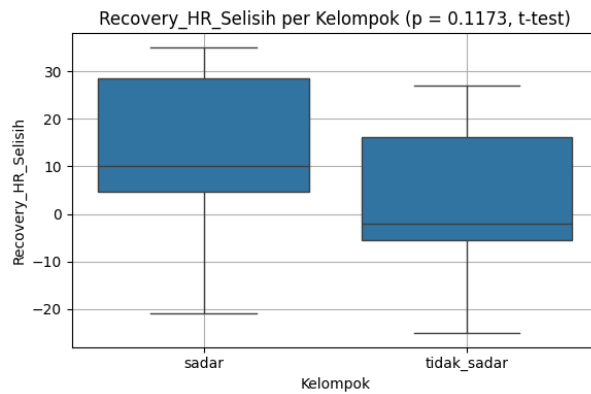
**Fig. 2.** Boxplot of Average Heart Rate (BPM) Based on Group

A This pattern of improved regulation was further validated by the data on calorie expenditure. Participants in the aware group burned significantly fewer calories during the hike compared to their unaware counterparts ( $p = 0.0120$ ). Rather than indicating underperformance, this difference reinforces the notion of metabolic efficiency. Equipped with real-time biometric insight, aware participants were able to adapt their exertion in accordance with terrain difficulty and bodily feedback. This facilitated the conservation of energy reserves while still completing the hike, ultimately demonstrating how feedback-enabled pacing strategies optimize physical output. As visualized in Figure 3, the boxplot highlights this statistically significant reduction in energy expenditure for the aware group.



**Fig. 3.** Boxplot of Calories Burned Between Groups

While the difference in heart rate recovery (HRR) between the two groups did not reach statistical significance ( $p = 0.1173$ ), the trend is notable. Participants in the aware group generally exhibited faster recovery times following exertion, a possible indication of improved cardiovascular adaptation. This suggests that real-time awareness may support more rapid physiological recalibration post-activity. One illustrative case involved Subject E, who experienced a sharp HR decline followed by steady recovery, a pattern potentially linked to feedback-guided regulation and self-pacing. The overall distribution of recovery differences is depicted in Figure 4.



**Fig. 4.** Boxplot of Recovery Heart Rate Difference (Post–Pre)

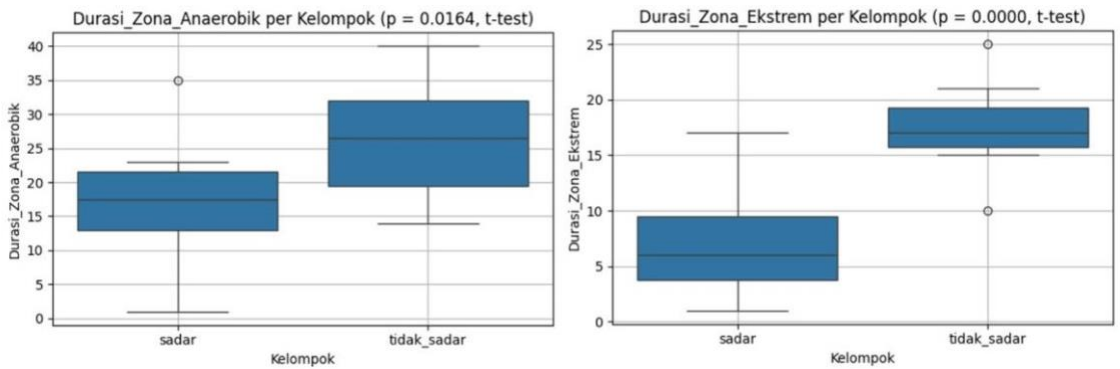
In contrast, passive physiological indicators such as oxygen saturation ( $SpO_2$ ) and body temperature showed no statistically significant differences between groups ( $p = 0.372$  and  $p = 0.442$ , respectively). These findings imply that not all physiological metrics are equally responsive to behavioral feedback.  $SpO_2$ , in particular, is more susceptible to external environmental factors such as ambient oxygen and altitude, while body temperature may fluctuate due to solar exposure and sensor variability. Their lack of responsiveness underscores the importance of selecting feedback-sensitive physiological parameters when evaluating the efficacy of wearable interventions.

In summary, the results provide strong empirical support for the hypothesis that real-time feedback enhances exertional control and metabolic efficiency. The statistically significant reductions in heart rate and calorie burn among the aware group suggest a behaviorally mediated advantage conferred by biometric awareness. These findings, observed in a naturalistic mountain hiking context, reinforce the practical value of smartwatches in facilitating adaptive self-regulation and promoting efficient physiological responses during sustained outdoor exertion.

## 4.2 Adaptive Effectiveness

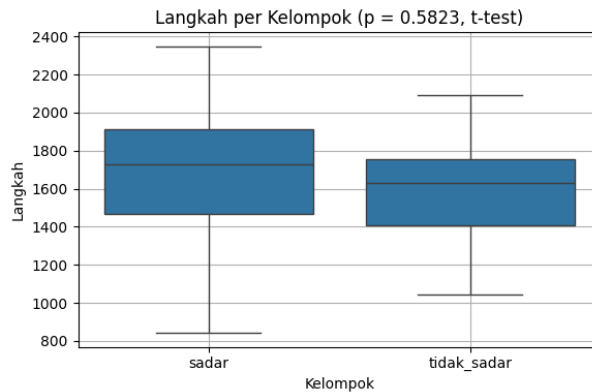
The analysis of adaptive effectiveness provides further insight into how real-time smartwatch feedback can influence users' behavioral strategies when navigating challenging physical terrain. Three core indicators were assessed to evaluate adaptive responses: time spent in specific heart rate training zones, total step count, and average hiking speed. These variables collectively reflect how participants adjusted their physical effort in response to internal cues and external trail conditions.

Among these indicators, the duration spent in high-intensity heart rate zones yielded the most pronounced group-level differences. Participants in the aware group spent significantly less time in the *extreme* heart rate zone ( $p = 0.0000$ ) and also demonstrated a statistically meaningful reduction in time spent in the *anaerobic* zone ( $p = 0.0164$ ). These results indicate that access to real-time biometric feedback enabled more refined pacing strategies, allowing individuals to avoid unsustainable intensity levels while maintaining consistent forward progress. Rather than reaching physiological thresholds unnecessarily, participants with feedback appeared to moderate their exertion, thereby reducing cardiovascular strain. These distinctions are clearly presented in Figure 5, which illustrates the between-group comparison of time spent in both extreme and anaerobic heart rate zones.



**Fig. 5.** Boxplot of Extreme & Anaerobic Heart Rate Zone Duration

In contrast, neither total step count ( $p = 0.5823$ ) nor hiking speed ( $p = 0.814$ ) exhibited statistically significant differences between the two groups. This suggests that the overall volume and velocity of movement were not directly influenced by awareness of biometric data. As shown in Figure 6, the step count distribution appears relatively balanced, implying that participants across both groups covered similar physical distances and terrain features. The absence of variation in these metrics indicates that behavioral adaptations were internal—focused on exertional pacing and physiological intensity—rather than manifesting as changes in stride count or hiking tempo.



**Fig. 6.** Boxplot of Total Step Count per Group

These findings reinforce the conclusion that smartwatch feedback primarily affects how participants manage effort intensity rather than gross physical output. Aware users demonstrated behavioral restraint, avoiding intensity spikes and modulating cardiovascular load without necessarily altering their step frequency or speed. In effect, their bodies moved the same, but in a more controlled and energy-efficient manner.

This aligns with self-regulation theory, which posits that external feedback facilitates the alignment of behavior with internal goals such as fatigue prevention and energy conservation. Moreover, in a demanding outdoor setting with steep terrain and variable elevation, this regulation becomes particularly critical. Participants without feedback likely relied solely on subjective perception or instinct, which proved insufficient for preventing overexertion, as evidenced by their prolonged presence in extreme HR zones.

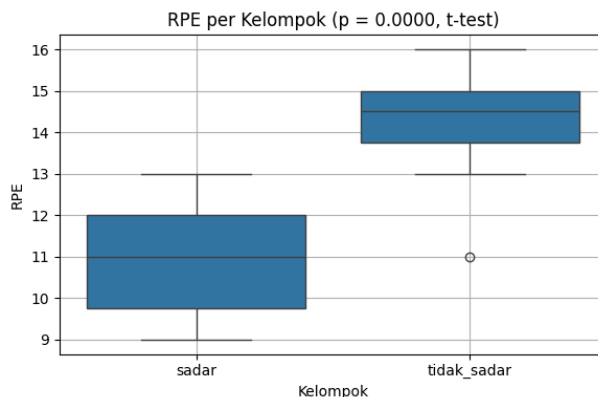
In summary, the data indicate that real-time awareness fosters a more adaptive response

to physical exertion. By consciously moderating intensity without compromising distance or time, participants in the aware group demonstrated a superior ability to balance endurance, safety, and energy expenditure—an outcome that has important implications for wearable technology design and implementation in outdoor endurance activities.

### 4.3 Perceptual Effectiveness

Perceptual effectiveness was assessed using the Borg Rate of Perceived Exertion (RPE), a psychophysiological measure that captures an individual’s subjective sense of effort during physical activity. The analysis revealed a statistically significant difference between groups, with the aware group reporting markedly lower average RPE scores compared to their unaware counterparts ( $p = 0.0000$ ). This finding suggests that real-time access to biometric feedback substantially enhanced the participants' ability to manage and modulate their perceived fatigue throughout the hiking task.

This distinction, visualized in Figure 7, supports the central hypothesis that physiological awareness not only influences objective metrics such as heart rate and calorie expenditure, but also plays a critical role in shaping subjective experience. Participants with access to smartwatch data appeared to interpret exertional cues more accurately, allowing them to self-regulate effort levels in response to perceived thresholds. In contrast, participants in the unaware group—lacking real-time insight into their physiological state—likely relied on less accurate internal estimations, resulting in greater reported fatigue.



**Fig. 7.** Boxplot of Mean RPE Score

From a self-regulation theory perspective, the ability to perceive exertion is not solely a function of physiological demand but is also mediated by attention, interpretation, and feedback loops. Feedback from wearable devices serves as an external reference point, reinforcing or recalibrating one’s perception of exertion. In the present study, this external input appears to have attenuated the psychological burden of physical strain, allowing participants in the aware group to experience the activity as less demanding despite comparable objective workloads.

It is also worth noting that perceived exertion serves as a powerful predictor of exercise adherence, safety, and performance. The lower RPE in the aware group indicates a more manageable physical experience, which may translate into higher motivation for continued physical activity in the long term a crucial implication for health interventions targeting young populations such as Generation Z.

Despite its significance, subjective perception is inherently variable and influenced by factors such as individual pain thresholds, motivation, and psychological readiness.

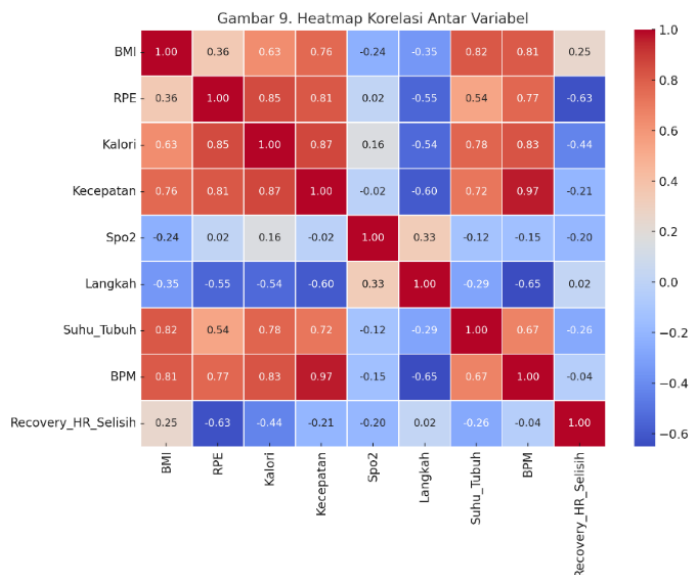
However, the consistency of lower RPE scores in the aware group, coupled with corresponding physiological efficiency, reinforces the integrative role of feedback in enhancing both behavioral and cognitive regulation.

In summary, the data demonstrate that smartwatch feedback not only improves physical regulation but also meaningfully reduces the psychological cost of exertion. This dual benefit underscores the value of perceptual monitoring in wearable technology design and highlights the importance of integrating both objective and subjective measures when evaluating exertional outcomes.

#### 4.4 Correlation Analysis

To explore the systemic relationships between physiological, behavioral, and perceptual responses, correlation analysis was conducted across key variables: average heart rate (HR), calorie expenditure, rate of perceived exertion (RPE), body mass index (BMI), oxygen saturation (SpO<sub>2</sub>), and walking speed. This integrative approach was designed to reveal how different facets of exertion and bodily response interact under varying levels of user awareness.

The correlation heatmap presented in Figure 8 illustrates several significant associations. Among the strongest correlations observed were between average heart rate and energy expenditure, and between calorie expenditure and RPE, each reaching statistical significance ( $p < 0.01$ ). These findings affirm that higher physiological output—manifested as increased cardiovascular load—directly translates into both greater metabolic cost and higher subjective fatigue. This alignment supports the construct validity of the measurement instruments used in the study and underscores the coherence between objective exertion and perceptual feedback.

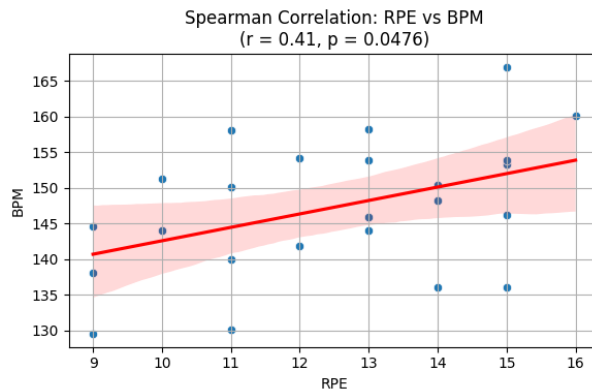


**Fig. 8.** Heatmap of Inter-Variable Correlations

One particularly notable correlation emerged between heart rate and RPE, visualized in the scatterplot in Figure 9. A significant positive relationship ( $p = 0.026$ ) indicates that as cardiovascular demand rises, so too does the subjective perception of effort. This

relationship was especially pronounced among participants in the unaware group, whose lack of feedback may have amplified the perceived difficulty of the task due to the absence of external context or regulatory cues.

In contrast, several variables failed to demonstrate meaningful associations. For instance, oxygen saturation showed no significant correlation with any other variable ( $p > 0.3$  across all pairs), suggesting that it was more influenced by environmental conditions such as altitude and ambient temperature than by exertional effort or self-regulation. Similarly, walking speed did not consistently correlate with perceived exertion or energy output, indicating that pacing behavior alone does not adequately reflect the physiological intensity of the activity.



**Fig. 9.** Scatterplot of Heart Rate vs Perceived Exertion (RPE)

These mixed results highlight the importance of selecting appropriate indicators when assessing physical performance and adaptive responses. Metrics like HR and RPE appear to capture core aspects of internal workload, while others such as  $SpO_2$  and speed may require contextual interpretation or complementary data to yield actionable insights.

From a methodological standpoint, the inclusion of both perceptual and biometric data strengthens the robustness of the analysis by providing a multi-dimensional understanding of exertion. The observed correlations lend further support to the hypothesis that wearable feedback mechanisms influence not just isolated variables but the broader interplay between body systems and subjective experience.

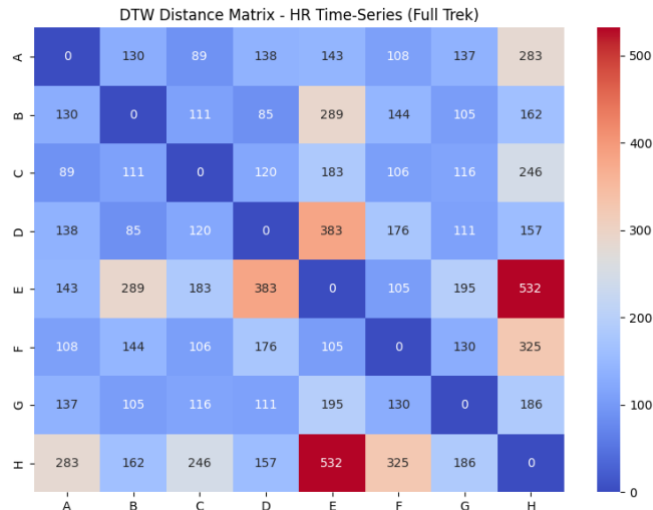
Overall, the correlation analysis demonstrates that exertional experience during hiking is governed by an intricate balance of cardiovascular effort, energy expenditure, and psychological perception. The strong internal alignment among key variables validates the analytical framework and underscores the regulatory benefits of real-time feedback in enhancing physiological and perceptual coherence.

#### 4.5 Dynamic Time Warping Analysis

To gain a deeper understanding of exertional rhythm and interindividual variability in cardiovascular response, Dynamic Time Warping (DTW) was employed to analyze heart rate (HR) time-series across the hiking route and its three elevation-based segments. This technique enabled temporal alignment of HR signals with varying pacing and durations, offering a robust lens for examining physiological synchronization between participants under different feedback conditions.

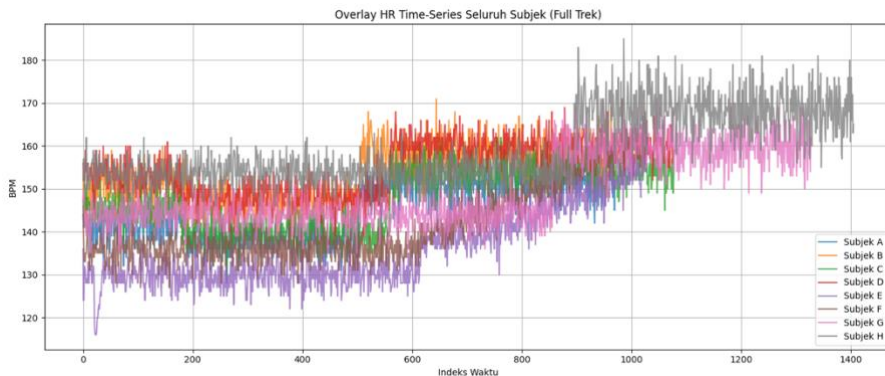
As depicted in Figure 10, the DTW distance matrix revealed consistently lower pairwise distances among participants in the aware group (A, C, E, G), signifying high similarity in their heart rate trajectories. This homogeneity reflects a shared regulation strategy likely

informed by conscious engagement with biometric feedback. In contrast, the unaware group (B, D, F, H) displayed wider variance and several high DTW values particularly between Subject H and E (distance = 532), and between D and E (distance = 383) indicating irregular pacing and disjointed cardiovascular responses in the absence of feedback mechanisms.



**Fig. 10.** Heatmap DTW Distance Matrix Between Subjects

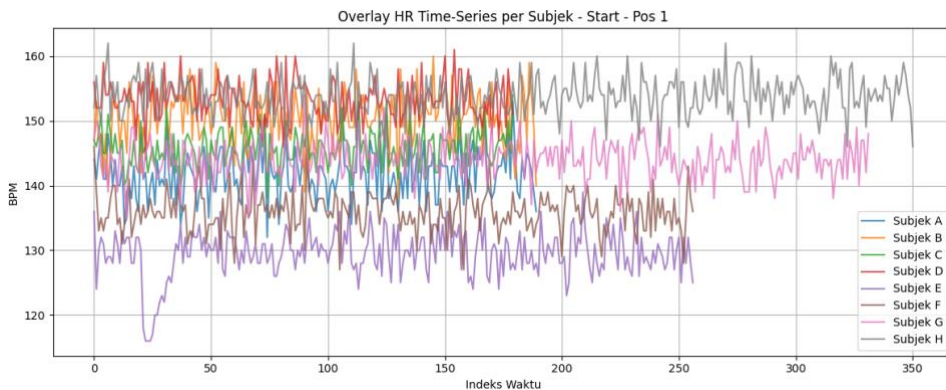
A deeper inspection of the full-route HR overlay in Figure 11 highlights this discrepancy. Participants in the aware group exhibited cohesive, moderately fluctuating HR patterns, characterized by adaptive oscillations in response to terrain elevation and effort demand. Conversely, participants in the unaware group demonstrated a mix of erratic and extreme profiles. Subject H, for example, showed an unnaturally flat and elevated HR throughout the hike, suggesting the onset of cumulative cardiovascular strain, possibly exacerbated by the absence of real-time regulatory cues. Meanwhile, Subject E, who received feedback, experienced a sudden HR drop mid-hike, documented in field notes as a nausea episode. The device successfully captured this anomaly, including the recovery phase, reinforcing the smartwatch’s sensitivity in detecting real-time deviations even under outdoor conditions.



**Fig. 11.** Overlay of HR Time-Series Patterns – All Subjects (Full Route)

Further insights are drawn from the segmental overlay during the Start to Pos 1 phase

(Figure 12). Here, early divergence in exertional strategy becomes apparent. Aware participants maintained synchronized pacing with moderated HR spikes, signaling a regulated physiological response to the initial ascent. In contrast, the unaware group exhibited premature peaks and inconsistent waveforms. Subject B, for instance, demonstrated a sharp HR increase early in the segment, while Subject D's curve fluctuated irregularly. Interestingly, Subject F, although in the unaware group, showed stable pacing throughout the segment, possibly reflecting intrinsic self-regulation or previous hiking experience.



**Fig. 12.** Overlay of HR Patterns: Start to Pos 1 Segment (Group Comparison)

These findings underscore the dual value of DTW and HR overlay visualization in revealing both group-level behavioral consistency and individual anomalies. The overall pattern suggests that conscious access to real-time feedback fosters aligned physiological regulation, especially under variable terrain and effort demand. The more stable HR patterns among aware participants indicate effective pacing modulation possibly driven by biofeedback-induced self-monitoring which helps prevent early overexertion and supports sustained cardiovascular control throughout prolonged activity.

From a methodological standpoint, DTW proves to be an insightful tool not just for recognizing alignment but for quantifying exertional variability and behavioral coherence in a way that static metrics like average HR or recovery values cannot capture. By incorporating both full-trail and segmental analysis, this study demonstrates the feasibility of using DTW to dissect exertional behavior in field settings, and offers a compelling case for integrating pattern-based analytics in future wearable technology evaluations.

## 5. Conclusion

This study confirmed that real-time biometric feedback from smartwatches significantly enhances the regulation of physiological responses during outdoor mountain hiking among Generation Z participants. Individuals granted visual access to smartwatch data demonstrated lower average heart rates ( $p = 0.0453$ ), reduced caloric expenditure ( $p = 0.0120$ ), and lower perceived exertion levels ( $p = 0.0000$ ), suggesting more efficient pacing strategies and effective energy management. Moreover, the application of Dynamic Time Warping (DTW) and HR overlay analysis revealed higher alignment in heart rate patterns among feedback-aware participants, indicating greater exertional stability and cardiovascular adaptation. These findings emphasize the pivotal role of conscious physiological monitoring in optimizing performance and managing fatigue during high-intensity physical activity.

The results also highlight the efficacy of combining wearable technology with pattern-based analysis methods such as DTW to uncover nuanced exertional rhythms, which are often obscured in traditional static measurements. Collectively, these insights contribute to the growing body of evidence that smartwatches, when used actively rather than passively, can function as reliable self-regulation tools aligned with the principles of physiological adaptation and behavioral awareness.

**Future Work.** Moving forward, several avenues warrant further exploration. First, it is recommended that smartwatch users actively engage with their biometric data rather than relying solely on passive observation. As demonstrated in this study, individuals who consciously interpreted physiological indicators such as heart rate, estimated caloric expenditure, and fatigue perception exhibited more stable cardiovascular regulation. Increasing users' literacy in interpreting biometric data and understanding its implications particularly when navigating extreme environmental conditions could empower more informed pacing strategies and performance decisions.

## References

- [1] R. Rustika, S. Driyah, R. Oemiati, and N. S. Hartati, "Predictors of Metabolic Syndrome: A Six-Year Prospective Cohort Study in Bogor, Indonesia," *Media Penelitian dan Pengembangan Kesehatan*, vol. 29, no. 3, pp. 215–224, 2019, doi: 10.22435/mpk.v29i3.654.
- [2] NCD Risk Factor Collaboration, "Diabetes. Evolution of diabetes over time," *The Lancet*.
- [3] S. Walzel et al., "Evaluation of Leading Smartwatches for the Detection of Hypoxemia: Comparison to Reference Oximeter," *Sensors*, vol. 23, no. 22, p. 9164, 2023, doi: 10.3390/s23229164.
- [4] Strava, "Year in Sport Trend Report," 2024. [Online]. Available: <https://press.strava.com/articles/strava-releases-year-in-sport-trend-report>
- [5] J. W. Navalta et al., "Wearable Device Validity in Determining Step Count During Hiking and Trail Running," *Journal for the Measurement of Physical Behaviour*, vol. 1, no. 2, pp. 86–93, 2018, doi: 10.1123/jmpb.2018-0010.
- [6] P. Martín-Escudero et al., "Are Activity Wrist-Worn Devices Accurate for Determining Heart Rate during Intense Exercise?," *Bioengineering*, vol. 10, no. 2, pp. 1–18, 2023, doi: 10.3390/bioengineering10020254.
- [7] Rakuten Insight, "Survey on wearable technology usage in Indonesia," Rakuten Insight. [Online]. Available: <https://goodstats.id/article/statistik-pengguna-wearable-tech-di-indonesia-QbR6I>
- [8] M. Siahaan, "Forecast of smartwatch users in Indonesia (2020–2029)," *Statista*. [Online]. Available: <https://www.statista.com/forecasts/1493570/indonesia-number-of-smartwatch-users>
- [9] Henriksen et al., "Using fitness trackers and smartwatches to measure physical activity in research: Analysis of consumer wrist-worn wearables," *Journal of Medical Internet Research*, vol. 20, no. 3, 2018, doi: 10.2196/jmir.9157.
- [10] Hughes et al., "Wearable Devices in Cardiovascular Medicine," *Circulation Research*, vol. 132, no. 5, pp. 652–670, 2023, doi: 10.1161/CIRCRESAHA.122.322389.
- [11] N. R. Haryana et al., "Generation Z Lifestyle in the Context of Eating Behavior, Stress Levels, Sleep Quality, and Its Relationship with Nutritional Status: Literature Review," *Jurnal Gizi Kerja dan Produktivitas*, vol. 4, no. 2, pp. 253–268, 2023, doi: 10.52742/jgkp.v4i2.195.
- [12] G. Cosoli et al., "Accuracy and Precision of Wearable Devices for Real-Time Monitoring of Swimming Athletes," *Sensors*, vol. 22, no. 13, 2022.
- [13] H. W. Nasution et al., "Building Employee Health Monitoring Tool Using IoT Oximeter in Palm Industry," *International Journal of Informatics and Computation*, vol. 7, no. 1, 2025, doi: 10.35842/ijicom.
- [14] K. D. Vohs and R. F. Baumeister, *Handbook of Self-Regulation: Research, Theory, and Applications*, 3rd ed., Guilford Press, 2016. [Online]. Available: <https://www.libgen.is/book/index.php?md5=C9AC7301A78B8E1B5D3543E65A7BE88A>

- [15] Warren, "Hiking as Nature's Therapy," 2020.
- [16] I. Kusuma, I. B. Putra, and I. G. D. Utamayasa, "Effectiveness of Smartwatch-Based Sensor Technology in Neuro Dance Exercise on Heart Rate, Blood Pressure, and Obesity Risk Prevention," *Jurnal Pendidikan Kesehatan Rekreasi*, vol. 9, no. 2, pp. 217–224, 2023. [Online]. Available: <https://ojs.mahadewa.ac.id/index.php/jpkr/article/download/2656/2106>
- [17] Bizzozero-Peroni et al., "Daily Step Count and Depression in Adults: A Systematic Review and Meta-Analysis," *JAMA Network Open*, vol. 7, no. 12, p. e2451208, 2024, doi: 10.1001/jamanetworkopen.2024.51208.
- [18] R. Varatharajan et al., "Wearable Sensor Devices for Early Detection of Alzheimer Disease Using Dynamic Time Warping Algorithm," *Cluster Computing*, vol. 21, no. 1, pp. 681–690, 2018, doi: 10.1007/s10586-017-0977-2.
- [19] F. Nurwanto, I. Ardiyanto, and S. Wibirama, "Light Sport Exercise Detection Based on Smartwatch and Smartphone Using k-Nearest Neighbor and Dynamic Time Warping Algorithm," in *Proc. 2016 8th Int. Conf. Inf. Technol. Electr. Eng. Empower. Technol. Better Future (ICITEE)*, pp. 2–6, 2017, doi: 10.1109/ICITEED.2016.7863299.
- [20] D. Boudreaux et al., "Validity of Wearable Activity Monitors during Cycling and Resistance Exercise," *Medicine & Science in Sports & Exercise*, vol. 50, no. 3, pp. 624–633, 2018, doi: 10.1249/MSS.0000000000001471.
- [21] Sulistyono and R. Djajasoepena, "Analysis of Sports Activity Recording Data on Wearable Devices," *INTEK: Jurnal Informatika dan Teknologi Informasi*, vol. 6, no. 1, pp. 1–7, 2023, doi: 10.37729/intek.v6i1.3049.
- [22] S. H. Mulyani, "Enhancing Mental Health Disorders Classification Using Convolutional Variational Autoencoder," *International Journal of Informatics and Computation*, vol. 6, no. 1, p. 1, 2024, doi: 10.35842/ijicom.v6i1.65.
- [23] S. Thomas et al., "Prediction of Peak Ground Acceleration (PGA) Using Artificial Neural Networks," *International Journal of Informatics and Computation*, vol. 6, no. 2, 2013.