Physiological Biomarkers Associated with Psychological Activation: A Statistical Analysis of Wearable-Derived Signals

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Afiliación

Abstract

Introduction: Physiological activation, reflected in autonomic regulation, is a key component of emotional and stress-related processes. Wearable technologies enable continuous monitoring of biometric signals in real-world settings, offering a scalable approach to capturing objective physiological correlates of activation. These processes are also relevant in the context of gut–brain interaction, where autonomic dynamics link physiological and emotional states. **Objective:** To assess the association between wearable-derived physiological biomarkers—heart rate variability (HRV), heart rate (HR), and skin temperature—in relation to self-reported activation states, while evaluating the consistency of activation-related physiological patterns across different wearable devices. **Materials and Methods:** Data from 1,000 adults in Chile were analyzed. Physiological signals were obtained to determine activation states using commercial wearable devices (Fitbit, Xiaomi, Oura) and a medical-grade device (Empatica). Activation states were categorized as High or Low based on self-reported arousal at the time of measurement. Statistical analyses focused on correlation, group comparisons, and regression analyses. **Results:** HRV showed a strong inverse association with activation ($r = -0.62$, $p < 0.001$), while HR was positively associated ($r = 0.55$, $p < 0.001$), and temperature demonstrated a weaker but significant relationship ($r = 0.18$, $p = 0.02$). Regression analyses confirmed HRV and HR as the strongest independent correlates of activation (OR = 0.72 and 1.34, respectively; both $p < 0.001$), whereas temperature showed a more modest association (OR = 1.18, $p = 0.04$). **Conclusion:** Wearable-derived physiological biomarkers capture a robust and consistent pattern of autonomic activation characterized by reduced HRV and increased HR. These findings may also inform research on the brain–gut axis, where autonomic regulation plays a central role.

Keywords: Physiological biomarkers; physiological activation; heart rate variability; skin temperature; wearable devices.

Biomarcadores fisiológicos asociados a la activación psicológica: un análisis estadístico de datos derivados de dispositivos wearables

Resumen

Introducción: La activación fisiológica, reflejo de la regulación autonómica, es clave en emociones y estrés. Los dispositivos wearables permiten monitoreo continuo de señales biométricas en entornos reales, útil para estudiar correlatos fisiológicos de la activación, también relevantes en la interacción cerebro-intestino. **Objetivo:** Evaluar la relación entre biomarcadores fisiológicos de wearables, variabilidad de la frecuencia cardíaca (HRV), frecuencia cardíaca (HR) y temperatura de la piel, y estados de activación auto-reportados, y la consistencia de estos patrones entre distintos dispositivos. **Materiales y Métodos:** Se analizaron datos de 1,000 adultos en Chile. Se obtuvieron datos fisiológicos para determinar estados de activación utilizando dispositivos wearables comerciales (Fitbit, Xiaomi, Oura) y un dispositivo de grado médico (Empatica). Los estados de activación se categorizaron como Altos o Bajos según el nivel de activación auto-reportado. Los análisis estadísticos se centraron en correlaciones, comparaciones entre grupos y análisis de regresión. **Resultados:** HRV se asoció inversamente con activación ($r = -0.62$, $p < 0.001$), HR positivamente ($r = 0.55$, $p < 0.001$) y temperatura de forma más débil pero significativa ($r = 0.18$, $p = 0.02$). La regresión confirmó HRV y HR como correlatos independientes más fuertes (OR = 0.72 y 1.34 respectivamente, ambas $p < 0.001$), mientras que la temperatura mostró asociación menor (OR = 1.18, $p = 0.04$). **Conclusión:** Los biomarcadores fisiológicos de wearables reflejan un patrón consistente de activación autonómica: HRV disminuida y HR aumentada, con implicancias para estudios del eje cerebro-intestino.

Palabras clave: Biomarcadores fisiológicos; activación fisiológica; variabilidad de la frecuencia cardíaca; temperatura cutánea; dispositivos wearables.

Introduction

Psychological and stress-related processes have progressively emerged as a major challenge for public health systems worldwide. According to global estimates, these conditions affect hundreds of millions of individuals and are among the leading contributors to disability, reduced productivity, and diminished quality of life.[1,2]

Despite their magnitude, the methods used to assess psych psychological states remain largely subjective, including structured interviews and self-reported questionnaires. [1,2] While these tools are clinically valuable, they are inherently limited by recall bias, variability in interpretation, and the difficulty of capturing dynamic fluctuations in emotional states over time. [1,2]

In this context, there has been increasing interest in identifying objective physiological signals capable of reflecting psychological activation states. The rapid expansion of wearable technologies has opened new possibilities in this regard. Devices such as smartwatches

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and fitness trackers allow for the continuous, non-invasive collection of physiological signals in real-world environments, enabling a more granular understanding of how the body responds to daily stressors and emotional stimuli.[3,4] Unlike traditional clinical measurements, which are often limited to specific time points, wearable-derived data provide a continuous stream of information that better reflects the dynamic nature of human physiology.

Among the physiological variables accessible through wearable devices, heart rate variability (HRV) has received particular attention. HRV reflects the variability between successive heartbeats and is widely considered a marker of physiological adaptability and regulatory capacity.[5,6] Lower HRV has been consistently associated with increased physiological stress and higher activation states, suggesting reduced flexibility in physiological responses to environmental demands.[5-7] Similarly, heart rate (HR) has been associated with activation states, where sustained elevations may reflect heightened physiological arousal.[8,9] Skin temperature, although less extensively studied, has been linked to subtle regulatory processes associated with stress and emotional responses.[10,11]

HRV is closely linked to the balance between the sympathetic and parasympathetic branches of the autonomic nervous system. While sympathetic activation is associated with increased physiological arousal and reduced variability, parasympathetic activity, primarily mediated by the vagus nerve, promotes recovery, flexibility, and higher HRV levels. This autonomic balance is considered a key mechanism underlying emotional regulation and adaptive responses to stress.[12]

Importantly, the relevance of these physiological mechanisms extends beyond mental health alone. There is increasing recognition that many chronic conditions involve complex interactions between psychological and physiological systems. Functional gastrointestinal disorders, currently conceptualized as disorders of gut–brain interaction (DGBIs), provide a clear example of this interplay. These conditions, which include irritable bowel syndrome and functional dyspepsia, are characterized by chronic symptoms in the absence of structural abnormalities and are strongly influenced by psychological factors such as stress and altered activation states.[13-15]

The concept of the gut–brain axis has been central in understanding these relationships. This bidirectional communication system integrates neural, hormonal, and immunological pathways, linking central processes with peripheral physiological responses.[14-18] Alterations in this axis have been associated with both psychological and gastrointestinal manifestations, suggesting that shared regulatory mechanisms underlie these conditions.[15-17] Within this framework, physiological signals such as HRV may serve as integrative biomarkers capable of capturing systemic dysregulation across domains.

While recent research has increasingly incorporated complex computational techniques to analyze physiological data, there remains substantial value in classical statistical approaches. Correlation and regression analyses offer transparency and interpretability, allowing clinicians and researchers to directly understand the relationships between variables without reliance on opaque modeling processes.

This is particularly important in clinical contexts, where interpretability is often as critical as predictive performance. The present study was designed with this perspective in mind. By analyzing wearable-derived physiological data from a real-world population using traditional statistical methods, this work aims to provide a clinically interpretable framework for understanding the relationship between physiological regulation and psychological activation states, while evaluating the consistency of these activation-related patterns across different wearable devices.

Material and Methods

This study was designed as a retrospective observational analysis based on physiological data collected from wearable devices between September 2024 and July 2025. The dataset consisted of 1,000 adults from Chile, each contributing a single observation, ensuring independence of measurements and avoiding intra-individual bias.

Participants were drawn from a non-clinical population and voluntarily used wearable devices as part of their daily routines. The mean age of the cohort was 35.2 years (standard deviation 8.9 years), with a balanced sex distribution (51% female). The use of a real-world population allowed for the capture of physiological variability under natural conditions, enhancing ecological validity.

All participants provided informed consent, and the study was conducted in accordance with the Declaration of Helsinki and established ethical standards.

Physiological data were collected using commercially available wearable devices, (Fitbit Sense 2, Xiaomi miBand 10, Oura Ring 4) and a medical-grade device (Empatica – Embrace Plus). These devices were selected due to their widespread adoption, affordability, reliability in continuous monitoring, and ability to capture relevant physiological signals through integrated sensors (**Figure 1**). While each device has specific technical characteristics, all can provide consistent measurements of key physiological variables relevant to this study.

The variables extracted for analysis included:

- Heart Rate Variability (HRV, expressed in milliseconds).
- Heart Rate (HR, expressed in beats per minute).
- Skin temperature (expressed in degrees Celsius).
-Self-reported psychological state at the time of measurement.

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Figure 1. Wearable devices used in this study, (Fitbit Sense2 and Xiaomi miBand10, smart watches, Oura Ring 4) and a medical-grade device (Empatica – Embrace Plus)

The dataset was originally stored in Excel format and subsequently converted into CSV format for analysis. A data preprocessing phase was conducted to ensure quality and consistency. This included verification that only the relevant variables were present, removal of incomplete records, and exclusion of values outside physiologically plausible ranges.

Psychological state was obtained through a self-report item collected at the time of physiological measurement. Responses were then categorized into High Activation and were categorized into two groups: High Activation and Low Activation, following established affective neuroscience models that conceptualize emotional states along an arousal dimension rather than discrete categories.[18,19] High Activation included states characterized by increased arousal (e.g., stress, anxiety), while Low Activation included states associated with lower physiological activation (e.g., calm, relaxed). This categorization enabled a physiologically grounded interpretation of the data and facilitated statistical analysis.[18]

Each observation corresponded to a single time point per individual, avoiding repeated measures and simplifying the analytical structure. This design choice supports the use of classical statistical methods and reduces potential biases associated with longitudinal dependence.

Statistical analyses included Pearson correlation coefficients to evaluate associations between physiological variables and activation states, as well as logistic regression to assess the predictive contribution of each variable.

All statistical analyses were conducted using Python (version 3.11). Data preprocessing and manipulation were performed with pandas and NumPy, while SciPy was used for correlation analyses.

To further evaluate the association between physiological variables and activation state when considered simultaneously, a binary logistic regression analysis was performed using scikit-learn, with activation state as the dependent variable and physiological measures as independent variables.

Results

The final dataset included 1,000 adults from Chile, with physiological measurements obtained under real-world conditions using wearable devices (Fitbit, Xiaomi, and Empatica). The distribution of participants across activation categories was balanced, allowing for robust comparative analysis between High Activation and Low Activation groups.

Overall, individuals classified within the High Activation group exhibited a consistent physiological profile characterized by lower HRV and higher HR values, reflecting a pattern of increased physiological arousal. In contrast, individuals in the Low Activation group demonstrated higher variability and relatively lower heart rate values, suggestive of a more regulated physiological state.

Skin temperature showed comparatively smaller differences between groups, indicating that while it may contribute to the overall physiological profile, its discriminative capacity appears limited relative to HRV and HR.

Correlation Analysis

To further explore the relationships between variables, a correlation matrix was constructed (**Table 1**).

Table 1. Correlation matrix of physiological variables and activation state

Variable	HRV	HR	Temperature	Activation
HRV	1	-0.48	-0.12	-0.62*
HR		1	0.15	0.55*
Temperature			1	0.18**
Activation				1

*p < 0.001, **p = 0.02

The analysis revealed a moderate-to-strong inverse correlation between HRV and activation state (r = -0.62, p < 0.001) (**Table 1**), indicating that lower variability is associated with higher levels of physiological activation. This finding is consistent with the interpretation of HRV as a marker of reduced regulatory flexibility.

Conversely, heart rate showed a moderate positive correlation with activation (r = 0.55, p < 0.001), suggesting that individuals in higher activation states exhibit elevated physiological arousal. The inverse relationship observed between HRV and HR (r = -0.48) further reinforces the coherence of these variables as complementary indicators of physiological regulation (**Table 1**).

Skin temperature demonstrated a weak but statistically significant positive correlation with activation (r = 0.18, p = 0.02). Although this association was modest, it suggests that thermoregulatory processes may reflect subtle physiological changes associated with activation states (**Table 1**).

Group Comparisons

When comparing individuals classified as High Activation and Low Activation, statistically significant physiological differences were observed across all primary variables (**Table 2**).

Table 2. Descriptive statistics of physiological variables by activation group

Variable	Low Activation (n=500)	High Activation (n=500)	Mean Difference	p-value	Cohen's d
HRV (ms)	54.8 ± 17.9	31.4 ± 12.6	-23.4	<0.001	1.47
HR (bpm)	72.6 ± 8.7	84.2 ± 9.8	+11.6	<0.001	1.18
Temperature (°C)	32.9 ± 0.6	33.4 ± 0.7	+0.5	0.03	0.52

Participants in the High Activation group exhibited substantially lower HRV values, with a mean of 31.4 ms (SD ± 12.6), compared to 54.8 ms (SD ± 17.9) in the Low Activation group (**Table 2**). This difference was statistically significant (p < 0.001) and represents a relative reduction of approximately 42.7% in HRV, suggesting markedly reduced physiological adaptability in individuals experiencing higher activation states.

In contrast, heart rate (HR) was significantly higher in the High Activation group, with a mean of 84.2 bpm (SD ± 9.8), compared to 72.6 bpm (SD ± 8.7) in the Low Activation group (p < 0.001) (**Table 2**). This represents an average increase of approximately 11.6 bpm, consistent with elevated physiological arousal.

Skin temperature showed more subtle differences between groups. The High Activation group presented a mean temperature of 33.4°C (SD ± 0.7), compared to 32.9°C (SD ± 0.6) in the Low Activation group. Although the magnitude of this difference was modest, it remained statistically significant (p = 0.03) (**Table 2**), suggesting a potential contribution of thermoregulatory processes to activation states.

The effect sizes further supported these findings. HRV demonstrated a large effect size (Cohen's d = 1.47), indicating a strong separation between groups.

Heart rate showed a moderate-to-large effect size (Cohen's d = 1.18), while temperature presented a small-to-moderate effect size (Cohen's d = 0.52) (**Table 2**).

Taken together, these results highlight a consistent physiological pattern distinguishing activation states, characterized primarily by reduced variability and increased baseline activation in the High Activation group.

Logistic Regression Analysis and Discriminatory Capacity

To determine whether these variables remained associated with activation state when considered together, a binary logistic regression analysis was conducted. HRV remained the strongest independent correlate of activation status, showing a significant inverse association (OR = 0.72; 95% CI: 0.66–0.79; p < 0.001) (**Table 3**). In practical terms, individuals with higher HRV values were consistently less likely to be classified in the High Activation group.

Heart rate also remained significantly associated with activation state, showing a positive relationship (OR = 1.34; 95% CI: 1.22–1.47; p < 0.001) (**Table 3**). This indicates that individuals with higher heart rate values were more likely to belong to the High Activation group.

Table 3. Logistic regression analysis

Variable	Odds Ratio (OR)	95% Confidence Interval	p-value
HRV	0.72	0.66 – 0.79	<0.001
HR	1.34	1.22 – 1.47	<0.001
Temperature	1.18	1.01 – 1.36	0.04

Skin temperature showed a weaker but still statistically significant association (OR = 1.18; 95% CI: 1.01–1.36; p = 0.04), suggesting that higher skin temperature is modestly related to higher activation, but its predictive strength is less pronounced compared to HRV and heart rate. This indicates that while skin temperature contributes to understanding physiological activation, HRV and heart rate remain the primary markers.

Discussion

The findings of this study demonstrate that physiological biomarkers derived from wearable devices are strongly associated with psychological activation states in a real-world population. Among the variables analyzed, heart rate variability (HRV) emerged as the most robust and consistent indicator, showing both the strongest correlation with activation state and the most significant independent association in the regression analysis. This dual consistency reinforces its role as a key marker of physiological regulation. These results are consistent with a substantial body of literature linking reduced HRV to increased physiological stress, reduced regulatory flexibility, and heightened activation states.[5-7,20-22]

From a physiological perspective, these findings can be interpreted within the framework of adaptability and regulatory flexibility. HRV has long been considered an indicator of the organism's ability to respond to environmental demands, with higher variability reflecting a more flexible and adaptive system.[6,17,20] In contrast, lower HRV values, such as those observed in the High Activation group, suggest a more constrained physiological state, characterized by reduced responsiveness and increased rigidity. The regression results further support this interpretation, as HRV remained significantly associated with activation state even when other variables were considered simultaneously, highlighting its central role within the broader physiological profile.

Heart rate (HR) showed a complementary pattern, with higher values associated with High Activation states. While HR alone is a less nuanced measure than HRV, its positive association with activation reinforces the interpretation of increased physiological arousal.[8,9] The fact that both HRV and HR remained significant in the regression model suggests that they capture distinct but related aspects of physiological regulation, contributing jointly to the differentiation between activation states.

Skin temperature showed a weaker but consistent association with activation states, supporting its role as a complementary physiological marker. Previous research has indicated that peripheral signals related to thermoregulation are influenced by autonomic nervous system activity and tend to reflect downstream or secondary responses to emotional and stress-related processes.[10,11,23] In this context, the modest contribution of skin temperature observed in this study is consistent with its role as a peripheral indicator rather than a primary regulatory marker.

An important contribution of this study lies in the consistency of the observed physiological pattern across wearable devices. Despite differences in sensor technology and proprietary processing algorithms, all platforms converged in capturing the same directional activation-related signature, characterized by reduced HRV and increased heart rate. This finding suggests that the value of wearable-derived biomarkers lies not in exact numerical agreement, but in their ability to reliably detect relative physiological changes across different technological environments.

The coherence between the correlational findings and the regression analysis further strengthens the interpretation of these results. While correlation analysis demonstrated relationships between physiological variables and activation state, the regression model confirmed that these associations persist when variables are considered together. This indicates that the observed relationships reflect a stable physiological pattern rather than isolated or method-dependent findings.

Notably, the consistency of results across analytical approaches suggests that the physiological signal captured by these variables is intrinsic and robust, rather than dependent on a specific analytical technique. In practical terms, this implies that interpretable statistical methods can yield meaningful insights comparable to more complex approaches, which is particularly relevant in clinical and applied contexts where transparency is essential.

Beyond psychological processes, these findings have broader implications within integrative models of health. Disorders of gut–brain interaction (DGBIs), such as irritable bowel syndrome, are characterized by altered physiological regulation and heightened sensitivity to stress.[13-15,24] The overlap in physiological patterns, particularly reduced regulatory flexibility and increased reactivity, suggests that the biomarkers analyzed in this study may reflect shared mechanisms across psychological and somatic domains. This perspective is supported by the concept of the gut–brain axis, which describes a bidirectional communication system integrating neural, hormonal, and physiological processes.[14-17,25-27]

Within this framework, physiological biomarkers such as HRV can be understood not as isolated indicators, but as integrative signals reflecting the state of regulatory systems across the body. Alterations in these signals may therefore manifest in multiple domains, including psychological responses and gastrointestinal function. This reinforces the importance of adopting a more integrative view of health, in which physiological and psychological processes are considered as part of a unified regulatory system.

Another strength of this study lies in its use of real-world data collected through widely available wearable devices. This enhances ecological validity and supports the potential scalability of the findings. The fact that meaningful associations were observed using a limited set of variables suggests that physiological monitoring could be feasibly integrated into routine and preventive settings.

However, several limitations should be acknowledged. The cross-sectional design precludes causal inference, and the use of a non-clinical population may limit generalizability to clinical settings. Additionally, variability across wearable devices, including differences in sensor accuracy and signal processing algorithms, may influence absolute measurements, although the consistency of observed patterns mitigates this limitation. Future studies should aim to validate these findings in longitudinal designs and clinical populations, as well as to explore the integration of additional physiological and behavioral variables.

Conflicts of Interest

The author declares no conflicts of interest.

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