Enhancing stress detection through HRV in wearable technology

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Abstract

Heart rate variability (HRV), a well-known biomarker for stress and an indicator of autonomic nervous system function, is being used more and more in wearables these days to identify stress. However, these devices' current HRV-based algorithms still have poor accuracy and reliability. This study presents a systematic review of HRV-based stress detection methods, focusing on research mostly published after 2016. A total of 35 articles were reviewed, with 23 studies meeting the inclusion criteria. The review categorizes stress detection approaches based on the integration of HRV with other physiological stress biomarkers (e.g., skin conductance, blood pressure) and the use of multi-modal sensor systems. Key findings reveal that combining HRV with additional biomarkers enhances the precision of stress detection, although challenges remain in achieving consistent results across diverse populations and conditions. The use of multi-sensor approaches, including wearable and non-invasive technologies, has shown promise but requires further validation in real-world settings. This review shows a structured overview of advancements in HRV-based stress detection, including a detailed summary of the settings, validation methods, and performance metrics of the included studies. These findings offer valuable insights for future research and the development of more robust and reliable wearable stress monitoring technologies.

Key words: Heart Rate Variability (HRV), Real-time stress monitoring , wearable technology, physiological biomarkers.

1 Introduction

One well-known indicator of autonomic nervous system (ANS) function and a non-invasive stress biomarker is heart rate variability (HRV). The dynamic interaction between the sympathetic and parasympathetic branches of the ANS causes variations in HRV, which represent the body's capacity to react to stress and recover. Lower HRV indicates reduced adaptability of the ANS, reflecting a diminished ability to respond to and recover from stress, which is not desirable as it is linked to numerous health problems, such as heart disease, mental health conditions, and cognitive decline. HRV analysis has consequently emerged as a key component of stress identification and health monitoring.(9)

This biomarker is used by wearable technology to identify stress in real time, providing continuous, non-invasive data collecting under real-world circumstances. However, because these devices rely on oversimplified algorithms, such as RMSSD or LF/HF ratios, that are unable to adequately reflect the complexities of heart rate dynamics, their accuracy is constrained. Furthermore, wearable technology is less reliable due to external distracting variables such as motion artefacts, hydration, and sleep quality, which introduce noise and variability into the data. These factors make it difficult to interpret results accurately, as they can mask real stress-related HRV changes or introduce false positives and negatives.(18)

Stress is a widespread problem in contemporary culture that has an impact on the physical and emotional well-being of people of all backgrounds. Timely intervention and the prevention of health issues connected to stress depend on accurate stress monitoring. Stress detection is a multifaceted challenge due to the complex interplay of physiological, psychological, and environmental factors influencing stress responses. This complexity requires the integration of various physiological biomarkers to complement heart rate variability (HRV) data. For example, a more thorough evaluation of stress can be obtained by combining HRV with measurements of skin conductance or cortisol, which capture multiple aspects of the stress response, including autonomic activation, hormonal changes, and behavioural reactions.(1)(15)

2 Problem statement

The effects of stress on a person's physical, mental, and emotional health are significant and widespread. Effective stress monitoring is necessary to enable timely interventions that reduce its harmful impacts. Wearable technology, which provides continuous, non-invasive monitoring, is a promising method for stress detection. Nevertheless, there are a number of serious problems with the HRV-based wearable technologies currently in use.

Firstly, wearables frequently rely on oversimplified HRV measurements, such as RMSSD or LF/HF ratios, that fail to adequately capture the complex dynamics of stress. These metrics, while useful, do not reflect the non-linear and multifaceted nature of stress responses. Stress detection is inherently complicated due to the dynamic interplay of the sympathetic and parasympathetic nervous systems, which produce subtle variations in heart rate patterns that can only be understood through advanced or non-linear analytical methods. Simplified analyzes are insufficient to account for these complexities, thereby limiting the accuracy and reliability of stress monitoring.(18)

Additionally, the utility of HRV as a stand-alone biomarker is hampered by its sensitivity to external variables such as sleep quality, physical activity, hydration, and body position. These factors introduce noise into the data, making it difficult to interpret results consistently and accurately in real-world settings. Furthermore, current wearable systems are highly sensitive to measurement conditions, such as breathing patterns and motion artifacts, which further complicate standardization across devices and users.(16)(10)

Most wearable systems are based solely on HRV without integrating complementary physiological biomarkers that could enhance the precision of stress detection. Biomarkers such as electrodermal activity, respiratory rate, skin temperature, and blood pressure have demonstrated the potential to provide a more comprehensive assessment of stress responses.(19)

By analyzing the present HRV-based stress detection problems in wearable technology, determining the most widely used biomarkers for stress detection, and looking into how the addition of other physiological biomarkers can enhance HRV data to increase the reliability and accuracy of stress monitoring systems, this research seeks to overcome these constraints. By addressing these issues, this study seeks to advance the understanding of stress detection methodologies and contribute to the development of more effective and robust wearable technologies for stress monitoring.

3 Methodology

To address the limitations of HRV-based stress detection and explore complementary biomarkers, a systematic review was conducted. The process began with the identification of a key paper focusing on the integration of HRV with other physiological biomarkers for stress detection. Using this paper as a foundation, Research Rabbit was employed to find additional studies with similar topics, ensuring a comprehensive exploration of the field.

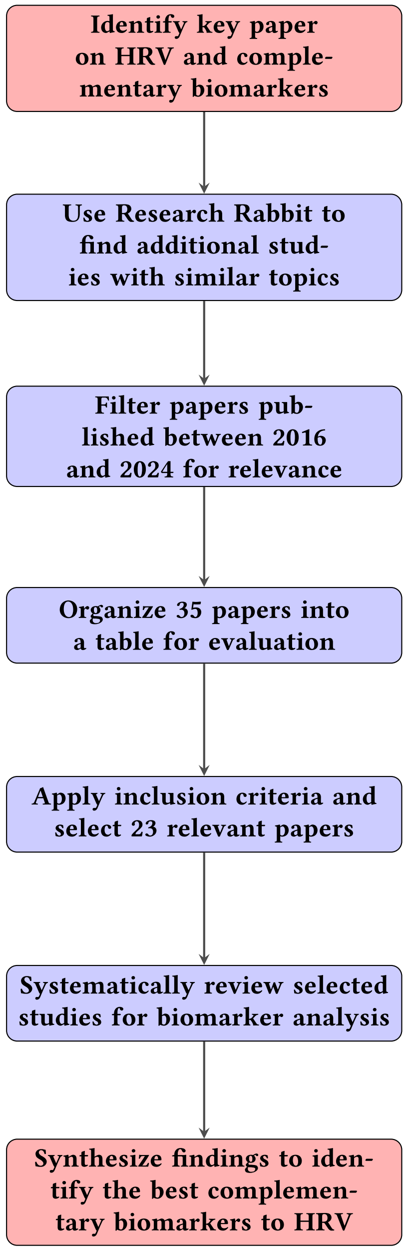
3.1 Study selection

To identify the latest developments in this quickly developing field of study, the search was limited to papers published between 2016 and 2024. This time frame was chosen due to the emerging nature of wearable stress monitoring technologies and the need for up-to-date information.

To make it easier to assess their relevance, a total of 35 papers were first found and arranged in a table. Predetermined inclusion criteria, such as the emphasis on HRV-based stress detection and the application of complementing physiological indicators, were used to evaluate each study. The other studies did not fit the particular criteria of this study, thus 23 of these were chosen to be included in the review.

3.2 Data analysis

To determine the most widely used biomarkers in wearable stress detection systems and assess their efficacy in conjunction with HRV, a systematic evaluation of the chosen papers was conducted. These findings were then synthesized to draw conclusions about the best complementary biomarkers to HRV and their potential to improve the precision and reliability of wearable stress monitoring systems. The methodology process followed in this study is visualized in Flowchart 1, providing a step-by-step overview of the systematic review approach.



Flowchart 1: *Methodology Process*

4 Biomarkers commonly used for stress detection

Physiological biomarkers, which offer quantifiable indications of the body's reaction to stress, form the foundation of stress detection. These biomarkers are crucial because they reflect alterations in key systems such as the respiratory, cardiovascular, autonomic, and other stress-related physiological functions. For this study, the selected biomarkers represent those most commonly used in wearable technology due to their practicality, reliability, and ability to capture diverse aspects of stress responses. Each biomarker was chosen based on its prevalence in wearable devices and its established role in the scientific literature as a reliable indicator of stress.(20)

Heart rate variability (HRV) is a commonly utilised biomarker for stress detection. Because HRV measures both acute and chronic stress reactions, it offers a thorough evaluation of autonomic nervous system (ANS) control. Its non-invasiveness and capacity to assess the interaction between the sympathetic and parasympathetic branches of the ANS, which yields data on resilience and adaptability, make it particularly valuable in wearable technology.(3)(16)

Electrodermal activity (EDA) is another significant biomarker. EDA detects changes in skin conductance brought on by sweat gland activity, which is closely related to arousal of the sympathetic nervous system. This biomarker is essential to real-time stress monitoring because it is very good at identifying acute stress and is extremely sensitive to sudden changes in emotional arousal.(2)

Respiratory rate (RR), which measures the number of breaths per minute, is also a key biomarker. Stress often leads to altered respiratory rhythms, such as irregular or increased breathing rates, which RR can accurately track. Wearables equipped with RR sensors can effectively monitor stress-induced changes in breathing patterns, offering another layer of information on physiological stress responses.(5)(4)

Blood pressure (BP), which increases under stress due to sympathetic activation and signifies the cardiovascular reaction to stress, is a measure of the force that circulating blood applies to blood vessel walls. Continuous blood pressure monitoring is now feasible because to recent developments in wearable technology, which greatly helps in stress detection initiatives.(6)(8)

Skin temperature (ST) is another critical biomarker, Skin offers information about localized physiological changes under stress by measuring changes in peripheral temperature brought on by stress-induced vasoconstriction. It is extremely helpful for continuous stress monitoring.((19)

Finally, stress-induced muscular tension has been evaluated using electromyography (EMG), a technique that evaluates muscle activity. EMG-enabled wearables can identify minute muscle reactions to stress, offering a different viewpoint on physiological arousal.(21)

A multimodal approach is crucial in stress monitoring technologies because stress is a complex phenomenon that manifests across multiple physiological systems. No single biomarker can capture the full spectrum of stress responses. By integrating biomarkers such as HRV, EDA, RR, BP, ST and EMG, wearable devices can provide a more comprehensive and accurate picture of an individual's stress levels, as demonstrated by research by Haque et al. (2024) (3), Costantini et al. (2023) (2), and Orini et al. (2017) (5).

5 Complementary biomarkers to HRV

Heart rate variability (HRV) is an invaluable tool to assess stress due to its ability to capture general autonomic regulation and provide insights into chronic stress patterns, resilience, and recovery.(1) However, HRV alone has limitations, such as its inability to detect acute stress reactions and localized physiological alterations, as it primarily measures overall autonomic balance rather than immediate responses. This requires the inclusion of complementary biomarkers to address these gaps and improve the precision of stress detection systems. (15)(3)

In this study, 11 scientific papers were reviewed, all of which involved HRV as a primary biomarker for stress detection. Among these, 3 papers also included electrodermal activity (EDA), and 3 others used respiratory rate (RR). As seen in Table 1 these two biomarkers emerged as the most studied and validated complements to HRV in wearable stress detection systems, and their inclusion has demonstrated substantial improvements in accuracy. For example, combining HRV with EDA or RR increases stress detection accuracy by 8-15%, according to the reviewed studies.

Biomarker	Number of Studies
HRV	11
EDA	3
RR	3
BP	-
ST	-
EMG	-

Table 1: *Biomarker usage across studies.*

5.1 Electrodermal Activity (EDA)

Sweat gland activity fluctuations, which are directly correlated with sympathetic nervous system arousal, are measured by EDA. Because of this, it is quite good at capturing acute stress reactions that HRV might miss on its own. Costantini et al. (2023)(2), for instance, showed that combining HRV and EDA in stressful situations, like driving, increased the accuracy of stress detection by 10-15%. This synergy occurs because HRV provides a more thorough picture of stress by capturing the larger dynamics of autonomic regulation, whereas EDA detects abrupt changes in arousal.

The ability of EDA to offer real-time input on acute stressors, like abrupt spikes in arousal brought on by outside stimuli, adds to its usefulness in wearable technology. To increase its dependability in practical situations, however, issues like noise brought on by variables like skin temperature or hydration levels demand further advances in algorithms and sensor technologies.(2)

5.2 Respiratory Rate (RR)

Another key indicator of stress is changes in respiratory rate (RR), which reflects modifications in breathing patterns brought on by the activation of the sympathetic nervous system. Research has demonstrated that adding RR to HRV-based models greatly increases sensitivity and specificity (Johnson et al., 2019; Orini et al., 2017). For instance, Haque et al. (2024) highlighted the complimentary significance of HRV by reporting an 8–13% increase in accuracy when RR data was paired with HRV.

RR is particularly effective at detecting transient stressors, such as irregular or elevated breathing rates during dynamic activities like driving or high-pressure tasks. By adding this real-time dimension to stress monitoring, RR enables systems to react quickly to acute stress events that HRV alone might overlook. Despite its potential, challenges such as measurement noise from physical activity or wearable device constraints highlight the need for further advances in sensor precision and algorithm development.

5.3 Why EDA and RR are the Best complements to HRV

The choice of EDA and RR as complementary biomarkers is supported by both their prevalence in the reviewed studies and their demonstrated impact on stress detection accuracy. Out of the 11 papers reviewed, EDA and RR each appeared in 3 studies, with consistent findings that their integration with HRV enhances the reliability and granularity of stress detection. Moreover, the reported accuracy improvements of 8-15% highlight their practical value in wearable devices. These findings are summarized in Table 1, which illustrates the distribution of biomarkers across the reviewed studies, and Table 2, which presents the accuracy percentages for HRV combined with EDA and RR.(2)(22)(23)

Combination	Average Accuracy (%)
HRV + EDA	88
HRV + RR	87
HRV + EDA + RR	90

Table 2: *Average Accuracy of HRV with Complementary Biomarkers.*

5.4 Limitations and Future Directions

While the combination of HRV with EDA and RR has proven effective, challenges remain, including noise from external factors (e.g., motion artifacts, hydration, or physical activity) and the limitations of current wearable technology in providing consistent, high-quality data. Future research should focus on developing robust algorithms and improving sensor technology to enhance the integration of these biomarkers. Exploring additional biomarkers, such as skin temperature or blood pressure, may further refine stress detection models and increase their utility across diverse real-world scenarios.

6 Conclusion and Discussion

This study has provided a comprehensive review of HRV-based stress detection methods and explored the potential of complementary biomarkers, specifically electrodermal activity (EDA) and respiratory rate (RR), to improve the accuracy and reliability of wearable stress monitoring systems. By systematically analyzing 11 scientific papers, it was observed that HRV remains the cornerstone of stress detection due to its ability to capture general autonomic regulation and chronic stress patterns (10). However, HRV alone is insufficient to address the full spectrum of stress responses, especially acute stressors and localized physiological alterations.

The inclusion of EDA and RR emerged as the most promising complementary approaches to HRV (2)(3). Both biomarkers demonstrated significant improvements in stress detection accuracy, with combined models showing an 8-15% increase in performance. EDA's sensitivity to rapid sympathetic nervous system allows the detection of acute stress events, while RR provides real-time insights into respiratory irregularities caused by stress. These findings were supported by studies such as those of Costantini et al. (2023) and Haque et al. (2024), which highlighted the complementary nature of these biomarkers in enhancing stress detection models.

Additionally, the systematic review revealed the prevalence of controlled experimental settings in stress detection studies, as outlined in Table 3, which documented 7 controlled settings and 4 natural settings. This highlights a research gap in validating these methods in real-world scenarios, an area that requires further exploration to ensure robustness and applicability in diverse environments.

Setting	Number of Studies
Controlled	7
Natural	4

Table 3: *Summary of Experimental Settings for Studies.*

Table 2 further demonstrated the performance metrics of combining HRV with EDA and RR, with the highest accuracy (90%) achieved when all three biomarkers were integrated (2)(22)(23). This underscores the importance of a multimodal approach in stress detection systems, as no single biomarker can fully capture the multifaceted nature of stress responses.

6.1 Future work

The findings of this review have significant implications for the development of next-generation wearable stress monitoring technologies. By integrating HRV with complementary biomarkers such as EDA and RR, manufacturers can improve the precision, reliability and applicability of their devices in the real-world(2). However, several challenges remain, including addressing noise from external factors, ensuring consistent data quality, and validating these systems in diverse populations and conditions.

In order to reduce noise and increase accuracy in wearable technology, future research should concentrate on advancing sensor technology. Better stress monitoring also depends on extending research into natural scenarios to confirm the efficacy of these methods in actual settings. Finally, investigating other biomarkers, such blood pressure and skin temperature, to improve stress detection models.

6.2 Conclusion

This study concludes by highlighting the importance of HRV as a basis for stress detection and the significant advantages of using complementary biomarkers such as RR and EDA. Wearable technology can open the door to better stress management and well-being for a variety of populations by overcoming present constraints and emphasising multimodal approaches.

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