**EPH- International Journal of Medical and Health Sciences**
Volume 12 Issue 4 October 2026
ISSN- 2456 - 6063
DOI: https://doi.org/10.67772/8fsxv629

# CLASSIFICATION OF HUMAN PHYSIOLOGICAL STATES USING HEART RATE, BLOOD PRESSURE, AND TEMPERATURE-BASED FEATURES

Nermeen Heshmat Azmy Fahmy[1]

[1]Badr Assuit University (BUA), Faculty of nursing, Lecture of medical surgical nursing. ORCID ID- 0009-0000-5181-1274, Email- nermeen.fahmy@bua.edu.eg

| Received:- 10/07/2026 | Revised:- 17/09/2026 | Accepted:- 05/10/2026 | Published:- 27/10/2026 |
|---|---|---|---|

**Abstract**
Physiological signals such as heart rate, blood pressure, and body temperature provide important information about changes in human functional states. Their combined assessment may improve differentiation among activity, recovery, resting, sleep, and breathing conditions. The study aims to characterize cardiovascular and thermal features across different human physiological states, examine their associations, and assess their contribution to physiological-state classification. A secondary data-based analytical study was conducted using 1,806 observations representing seven physiological states: Cardio, Cardio Recovery, Resistance, Resistance Recovery, Sedentary, Sleep, and Deep Breathing. Frequency and percentage were used for categorical variables, while continuous variables were summarized as mean ± standard deviation. Chi-square tests assessed associations between physiological states and pre-to-post changes. Pearson correlation evaluated relationships among selected physiological measures, and multinomial logistic regression examined independent associations with state membership. Distinct cardiovascular and thermal response patterns were observed across physiological states. Activity-related conditions showed greater physiological activation, whereas recovery, sleep, and deep-breathing states demonstrated different patterns of reduction or stabilization. Chi-square analysis showed significant associations between physiological state and changes in heart rate, blood pressure, skin temperature, and core temperature. Strong correlations were observed among several cardiovascular and thermal variables. Multinomial regression did not identify a stable single independent predictor. Combined heart rate, blood pressure, and temperature-based features effectively characterize differences among human physiological states and may support non-invasive physiological monitoring applications.

**Keywords:** Physiological states; Heart rate; Blood pressure; Body temperature; Multinomial logistic regression

## Introduction

Physiological monitoring is essential for gaining insight into alterations of the human physical, functional and behaviour states. Physiological signals can tell you objectively how your body reacts to activity, recovery, rest, environmental demands and psychological demands. Heart rate, blood pressure and body temperature are some of the most frequently monitored indicators and are particularly useful for heart rate and blood pressure indicate cardiovascular function and autonomic regulation, circulation, metabolism and thermoregulation. In the field of human physiology, there is a growing need for multimodal physiological monitoring to detect changes in human states in real-world situations, such as vigilance and behavioral responses (Koul et al., 2026).

Physiological monitoring is now more feasible and accessible due to the surge in the development of wearable devices and sensor-based systems. Physiological data are now increasing being used in the classification of various states of response using machine-learning techniques to identify complex patterns within the data. This has been applied successfully to stress classification and the associated physiological assessment (Fonda et al., 2024). Wearable based affect recognition has also showcased the value of physiological signals of continuous measurement for the detection of changes in human emotional and functional state (Schmidt et al., 2019).

Likewise, health-monitoring systems with IoT have integrated the physiological data with the predictive models for stress classification and vital-sign forecasting (Bhavani et al., 2022).

Thermal characteristics can be used to provide extra information that can be complementary with the cardiovascular information. With contactless thermal imaging, it has been found that there is a physiological response to stress which can be seen in changes in temperature, meaning that this could be an indication of autonomic activation and/or altered physiological regulation (Gioia et al., 2022). Another example of the use of wearable smart devices is adaptive emotion-recognition systems, which are based on physiological data collected during activities performed in daily life (Wang et al., 2020). Further, thermoregulatory responses were modeled to determine the human thermal sensations, under dynamic environmental conditions (Li et al., 2022). Other multimodal sensing approaches have been developed to classify human states, such as estimating cognitive load from a combination of heart rate, body temperature, and other physiological signals, reflecting the wider applicability of multimodal sensing for human-state classification (Romine et al., 2020).

However, there are key gaps in the published literature. Most of the physiological classification studies are based on a particular clinical, psychological or environmental outcome instead of on more general human physiological state classes. For instance, machine-learning solutions have been created to aid in clinical diagnosis in real-time, but these are predominantly disease-oriented and not aimed at distinguishing normal activity, recovery, rest and breathing states (Mahmud et al., 2026). Wearable devices reviews also highlight the measurement technology and individual vital parameters and the integrated analysis of both cardiovascular and thermal variables is comparatively limited (Jegan & Nimi, 2024). Much of the previous research also looks at specific physiological indices or at narrowly drawn outcomes. There are several studies that have made use of deep learning models to compare EEG, HRV, and EDA's predicting power for thermal comfort prediction, yet, these have mainly focused on assessing comfort in the environment and not recognizing general physiological state (Sahoh et al., 2026). Similarly, in the field of wearable sensing, pulse rate and skin temperature have been employed for prediction of personal comfort; however, there are no models which consider more than one activity and recovery state (Chaudhuri et al., 2020). Additionally, resting HR is affected by the environmental temperature, indicating a relationship between cardiovascular and thermal responses, but these effects have not been extensively assessed in combination with BP for physiological classification in multi-class. Consequently, there is still little evidence of the discriminatory power of heart rate, blood pressure, and various features based on temperature.

Different responses to activity, recovery, rest, sleep, and controlled breathing (heart rate, blood pressure, and temperature). Previous studies have indicated that physiological signals, such as cardiorespiratory measurements under various environmental conditions, can be used to give meaningful information about functional changes in the human body (Rodrigues et al., 2022). The HR-Temp correlation has proven to be useful for machine learning tasks as well (Lu et al., 2025). The synergy of multiple signals over a single parameter has also been successfully introduced into machine learning models for thermal-state prediction, with physiological variables added to the mix (Ho et al., 2024). Physiological data is also shown to have a high dependency on relevant variables in the field of feature extraction (Gouverneur et al., 2021).

This study thus puts into question the use of secondary physiological data to assess the ability to discriminate between various human physiological states based on cardiovascular and thermal parameters.

**Study Objectives**

1. To characterize heart rate, blood pressure, and temperature-based features across different human physiological states.
2. To determine the associations and discriminatory patterns of cardiovascular and thermal variables among physiological-state categories.
3. To develop and evaluate machine-learning models for classifying human physiological states using heart rate, blood pressure, and temperature-based features.

## 2. Materials and Methods

### 2.1 Study Design

A secondary data based analytical design was employed to investigate differences and relationships in cardiovascular and thermal measurements under various human physiological conditions. Analytical features were confined to physiological conditions (before and after) and included heart rate, blood pressure and temperature data. A multiclass analytical approach was used because the outcome variable encompassed seven different physiology states such as activity, recovery, resting, sleep and controlled breathing conditions.

### 2.2 Data Source

Physiological Signal Synthesis and Classification: Assessing Entropy Change and Other Physiological Signals data was used in the study and was obtained from the Mendeley Data website (Lee et al., 2025). It had 1,806

observations and 25 variables, such as cardiovascular and temperature measurements obtained under various physiological conditions. Task was the primary outcome variable with seven categories: Cardio, Cardio Recovery, Resistance, Resistance Recovery, Sedentary, Sleep, and Deep Breathing. All physiological states had the same number of observations, ensuring good representation of all study conditions.

### 2.3 Study Variables

The physiological state (Task variable) was the dependent variable. Pre and post state measures of heart rate, skin temp., core temp, and systolic and diastolic blood pressure were the main physiological variables. Other measurements were collected from the hands, legs, and head; however, for the most part the primary statistical comparisons were made for smartwatch heart rate, smartwatch blood pressure, skin temperature, and core temperature as these measurements were most relevant to the objective of the study.

### 2.4 Data Preparation

Data quality screening was performed prior to analysis of the original CSV file. To make the names of variables easier to understand, leading spaces were removed to be consistent across variables. The missing values and duplicate observations were evaluated and no missing values or duplicate observations were found. The file was therefore cleaned and all 1,806 observations and 25 variables were retained.

### 2.5 Statistical Analysis

Categorical data were presented as frequencies and percentages, and continuous data were presented as mean ± SD. Association between physiological state and pre-to-post changes was tested using chi-square tests and relationship between cardiovascular and thermal measures was tested using Pearson correlation. Selected predictors were assessed in their association with membership in the physiological-states in multinomial logistic regression using Cardio as the reference category. The results of the regression were presented in the form of β coefficients, odds ratios and p-values, where p-values less than 0.05 were considered statistically significant.

## 3. Results

### 3.1 Study Characteristics and Distribution of Physiological States

Seven physiological state categories were used in the analytical sample, including physical activity, recovery, resting, sleep and controlled breathing. These included Cardio, Cardio Recovery, Resistance, Resistance Recovery, Sedentary, Sleep, and Deep Breathing. They were subjected to a frequency distribution prior to other statistical comparisons, and the distribution by the seven states is shown in Figure 1.

**Table 1. Distribution of Human Physiological States**

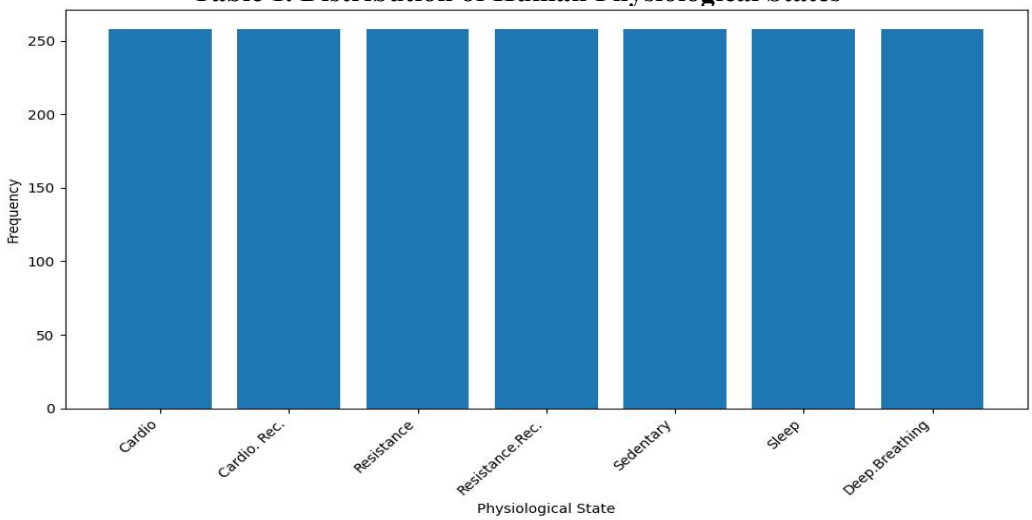



**Figure 1. Distribution of Human Physiological States**

Each category of the physiological states was equally represented as indicated in Figure 1. This uniform distribution reduced class imbalance and allowed a standardized response between cardiovascular and temperature-related responses in the various physiological conditions.

### 3.2 Overall Physiological Characteristics

Descriptive analysis revealed that there were visible differences between cardiovascular and thermal measurements taken before and after the state. There were smaller overall changes for systolic and diastolic blood pressure compared to heart rate, which showed an overall trend to increase after the recorded physiological conditions. A difference in skin and core temperature also existed between pre-state and post-state assessments, further reflecting thermal responses. The blood-pressure and temperature variables were less

variable than the heart-rate variable. Together, these results indicate that the physiological traits evaluated in this study provided meaningful variation in cardiovascular and thermoregulatory response to the study conditions. Table 1 presents the descriptive statistics for the selected measurements overall.

**Table 1. Overall Descriptive Statistics of Selected Physiological Features**

| Physiological Feature | Pre-State Mean ± SD | Post-State Mean ± SD |
|---|---|---|
| Smartwatch heart rate | 88.64 ± 20.63 | 90.71 ± 22.53 |
| Systolic blood pressure | 123.39 ± 5.69 | 122.10 ± 7.99 |
| Diastolic blood pressure | 82.58 ± 5.55 | 81.51 ± 7.57 |
| Skin temperature | 34.44 ± 1.54 | 34.63 ± 1.64 |
| Core temperature | 36.65 ± 0.82 | 36.85 ± 1.16 |

The mean difference between the pre-state and post-state values of the selected physiological features were plotted to provide a general comparison of the direction of changes in cardiovascular and thermal responses. The results for the comparative pattern of heart rate, blood pressure, skin temperature and core temperature are shown in Figure 2.

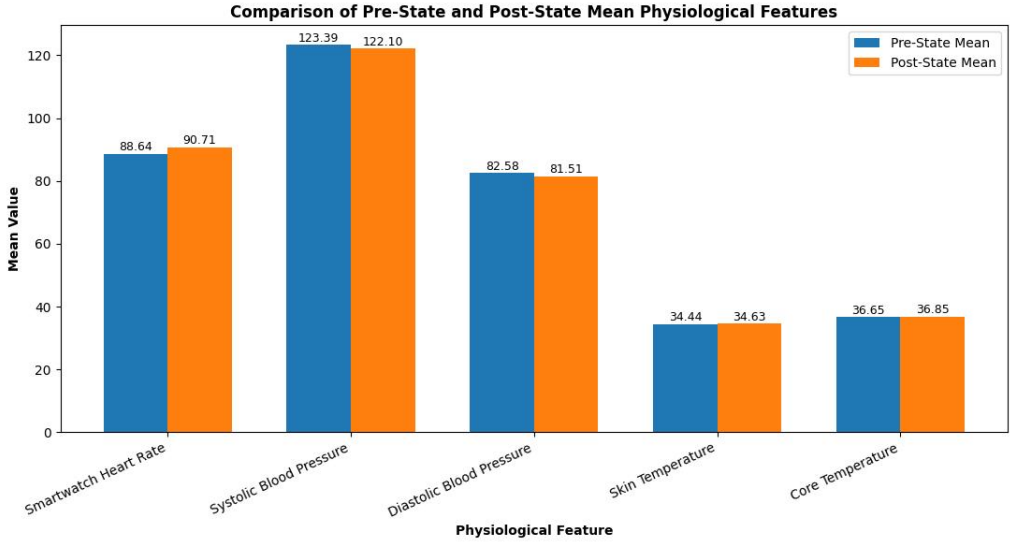



**Figure 2. Comparison of Pre-State and Post-State Mean Physiological Features**

The physiological features had varying responses to the pre-state and post-state measurements, as depicted in Figure 2. Both systolic and diastolic blood pressure were slightly reduced and heart rate and temperature measures were generally increased.

### 3.3 Physiological Features Across Different States

Different physiological patterns were seen for the various activity and resting conditions. Cardio and Resistance states were generally found to have a higher physiological activation, with cardiovascular and thermal measurements increasing from a pre to post state. However, on the other hand, there were decreases in some of the post-state measures for the corresponding recovery conditions, indicating a move toward physiological recovery. Stable responses were observed for Sedentary activity with reductions in HR and temperature-related measures for Sleep. Deep Breathing showed rather restricted heart-rate variability with decreases in blood-pressure and temperature readings. These results show clearly distinct state-specific physiological responses and the full comparisons of selected features are given in Table 2.

**Table 2. Physiological Features Across Human Physiological States**

| State | HR Pre | HR Post | SBP Pre | SBP Post | Skin Temp. Pre | Skin Temp. Post | Core Temp. Pre | Core Temp. Post |
|---|---|---|---|---|---|---|---|---|
| Cardio | 80.73 ± 4.24 | 121.31 ± 2.78 | 120.51 ± 0.31 | 129.41 ± 0.76 | 33.25 ± 0.15 | 34.78 ± 0.33 | 36.47 ± 0.05 | 37.95 ± 0.13 |
| Cardio Recovery | 127.02 ± 0.73 | 112.13 ± 1.02 | 129.41 ± 0.76 | 120.62 ± 1.49 | 36.17 ± 0.11 | 35.08 ± 0.14 | 36.53 ± 0.02 | 35.53 ± 0.28 |
| Resistance | 79.01 ± 4.23 | 112.56 ± 4.68 | 120.51 ± 0.31 | 134.48 ± 0.80 | 34.15 ± 0.14 | 36.63 ± 0.31 | 36.13 ± 0.06 | 38.59 ± 0.31 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Resistance Recovery | 112.30 ± 4.86 | 79.40 ± 3.57 | 134.50 ± 0.74 | 119.51 ± 0.64 | 36.69 ± 0.31 | 35.78 ± 0.32 | 38.59 ± 0.32 | 37.70 ± 0.33 |
| Sedentary | 76.59 ± 3.68 | 78.09 ± 3.68 | 120.51 ± 0.31 | 123.04 ± 0.56 | 35.05 ± 0.15 | 35.51 ± 0.21 | 36.03 ± 0.08 | 36.47 ± 0.16 |
| Sleep | 73.68 ± 4.09 | 61.13 ± 4.41 | 120.54 ± 0.59 | 118.99 ± 0.86 | 33.84 ± 0.15 | 33.08 ± 0.05 | 36.33 ± 0.06 | 35.63 ± 0.08 |
| Deep Breathing | 71.17 ± 4.90 | 70.32 ± 4.92 | 117.78 ± 0.88 | 108.67 ± 5.90 | 31.95 ± 0.15 | 31.55 ± 0.41 | 36.48 ± 0.07 | 36.08 ± 0.38 |

HR = heart rate; SBP = systolic blood pressure; Temp. = temperature.

### 3.4 Association Between Physiological State and Physiological Changes

Chi-square analysis revealed statistically significant relationships between physiological-state category and direction of the pre to post change for all cardiovascular and temperature-related variables evaluated. The associations of blood-pressure measures were especially strong with the classification of physiological state, and there were clear associations of heart rate, skin temperature, and core temperature with the physiological state classification. These results suggest that the increases and non-increases in one of the physiological measures were not random, but rather were systematic across activity, recovery, resting, sleeping, and breathing conditions. Thus, modifications in cardiovascular and thermal characteristics were highly related to the physiological state monitored. Detailed chi-square statistics and significance levels are given in Table 3.

**Table 3. Chi-Square Association Between Physiological State and Physiological Change**

| Variable | $\chi^2$ | df | p-value |
|---|---|---|---|
| Heart rate | 1629.466 | 6 | <0.001 |
| Systolic blood pressure | 1735.949 | 6 | <0.001 |
| Diastolic blood pressure | 1699.018 | 6 | <0.001 |
| Skin temperature | 1677.895 | 6 | <0.001 |
| Core temperature | 1669.480 | 6 | <0.001 |

### 3.5 Correlation Among Physiological Features

Several significant correlations between cardiovascular and temperature measures were found using Pearson correlation analysis. The highest correlation was found between measurements of systolic and diastolic blood pressure at the same assessment times, and heart rate was closely correlated with the pre-state blood-pressure measurements. Coordinated cardiovascular and thermal response was also noted in the relationship between blood pressure and both skin and core temperature. Some of the post-state variables were also moderately to strongly positively related. The overall correlation pattern between the selected physiological features is visually summarized in Figure 3.

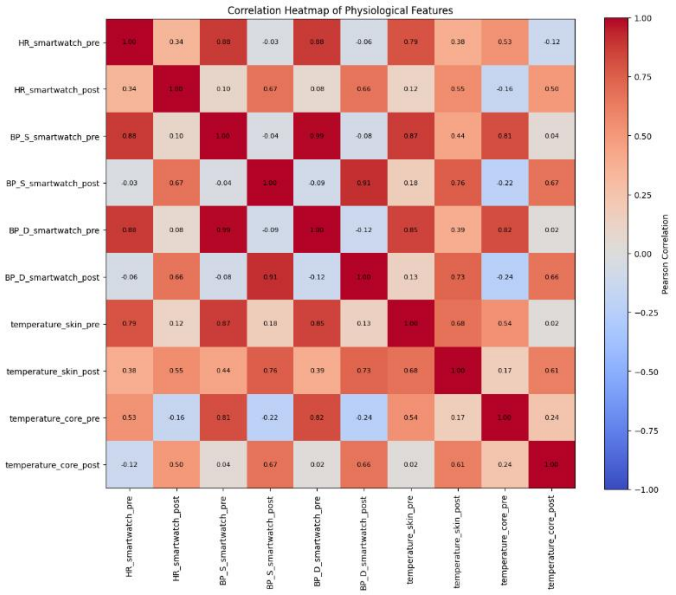



**Figure 3. Correlation Heatmap of Physiological Features**

The correlation matrix was mostly positive, with stronger correlation among the blood-pressure variables and some temperature variables, as seen in Figure 3. There were also some weak or negative relationships, which reflect that some physiological features did not respond consistently in the different conditions.

### 3.6 Multinomial Logistic Regression Analysis

Multinomial logistic regression was performed with Cardio as the reference category to identify if the cardiovascular and thermal features selected independently differentiated the physiological states. A few of the predictors had comparatively large positive or negative coefficients and odds ratios but were not statistically significant when simultaneously adjusted for the other variables in the model. Very wide confidence intervals were provided for estimates, which indicates limited stability of individual regression effects and a high level of uncertainty. However, none of the physiological measures alone predicted state membership in the multivariable model, even though there were definite state-specific differences in the previous analyses. The summary of selected regression estimates are given in Table 4.

**Table 4. Selected Multinomial Logistic Regression**

| Outcome vs Cardio | Predictor | β | Odds Ratio | p-value |
|---|---|---|---|---|
| Cardio Recovery | Pre heart rate | 4.680 | 107.806 | 0.9835 |
| Resistance | Post skin temperature | 8.701 | 6006.307 | 0.8590 |
| Resistance Recovery | Pre core temperature | 4.797 | 121.202 | 0.9894 |
| Sedentary | Pre skin temperature | 7.234 | 1386.372 | 0.9748 |
| Sleep | Post heart rate | -8.575 | <0.001 | 0.9574 |
| Deep Breathing | Post skin temperature | -6.652 | 0.001 | 0.9507 |

## 4. Discussion

The results of the present study show a distinct difference in cardiovascular and thermal responses among various physiological states. Activity-related conditions revealed trends of heightened levels of physiological activation, with fewer measures of desensitization in recovery. Sedentary and Sleep had comparatively less or lower responses and Deep Breathing had a characteristic pattern of lower HR response and decreased blood-pressure and temperature measures. The pronounced chi-square results also suggest that the nature of state observed was strongly related to the direction of the physiological change. Several cardiovascular and thermal variables were also found to be correlated, indicating that these variables are physiologically linked as opposed to being independent of each other. The multinomial regression, however, showed no a single statistically significant independent predictor, perhaps due to high collinearity and overlap among measured physiological variables.

The results in general agree with previous research showing that mixed cardiac and thermal data can provide information about variations in human physiology and behavior. Multivariate thermal features have been shown to be useful for human thermal comfort predictions (Li et al., 2025), suggesting that temperature-related signals can be useful for physiological-state discrimination. In a similar vein, Arsalan et al. (2022) identified a potential advantage of using more than one physiological signal when assessing stress, and pointed out that multimodal monitoring, in general, gives more information than single-signal monitoring. Thermal measures are also known to be useful indicators of the autonomic and psychophysiological response, especially when using infrared imaging to measure non-invasive temperature changes. The results of the present study are also similar to the increasing use of wearable systems for personalized physiological monitoring. Olyanasab and Annabestani (2024) highlighted how the combination of several biomedical signals is essential for wearable-device applications, as it can enhance the discriminatory power of the individual signals when they are not enough. Tai et al. (2024) also showed the coordinated changes of blood pressure, pulse rate, and skin temperature under the actual thermal exposure, which is consistent with the relationship between cardiovascular and thermal parameters in the present analysis. Moreover, Šalkevičius et al. (2019) demonstrated that the use of physiological signals allows for the distinction between anxiety-related states, thus highlighting potential for the use of multivariate physiological patterns for human condition change recognition. When considered as an integrated physiological profile, these previous studies together support the interpretation that the combination of cardiovascular and thermal features are more informative.

The results have a number of practical implications. First, the significant differences between the four activity states (activity, recovery, sleep and sedentary) and breathing indicate that signals routinely measured like HR, BP, skin temp, and core temp could be useful for non-invasive physiological monitoring. These measures might be used to design wearable systems for monitoring fitness, recovery, occupations, and personalized health applications. These good relationships between some of the different variables also suggest that integrated

monitoring could give a more complete picture of physiological response than single measurements. Meanwhile, the unstable regression estimates indicate that selection of highly correlated predictors should be done carefully when building a predictive model.

Some limitations are to be taken into account. The study relied on secondary data and the analysis was based on the original measurement procedures and variables available to the study. Potential confounder factors like age, sex, health status, environmental exposure, medication use, and fitness status were not included in the present analysis. There may also have been some high correlations between some of the predictors, which may have affected the stability of the multinomial regression model. Moreover, the results were obtained for a set of predetermined physiological conditions and may not necessarily reflect the more intricate and complex transitions between physiological conditions in real world settings.

The results of these studies should be confirmed with different populations and with real-time wearable measurements. Investigations should also be done to determine if removal of highly correlated predictors increases the stability of the regression and the accuracy of classification. Other physiological signals like heart-rate variability, respiratory rate, electrodermal activity, oxygen-saturation, and movement data could enhance state discrimination. In larger sample sizes, more sophisticated predictive methods might also be considered, as long as they are not too complicated to explain. In general, future research should aim for the creation of well validated and externalized systems that can reliably identify physiological states over long periods of time in natural environments.

## 5. Conclusion

The results of this research showed that HR, BPs, and T-based features carry useful information in discriminating human physiological states. State-specific patterns were seen clearly in Cardio, Cardio Recovery, Resistance, Resistance Recovery, Sedentary, Sleep and Deep Breathing. The activity-related states exhibited higher cardiovascular and thermal activation, while the recovery and sleep conditions yielded some decreases in the post-state measures. Deep Breathing also exhibited a unique pattern of physiological response, with contrast to the other states. Chi-square results showed that the observed pre-to-post change in heart rate, systolic BP, diastolic BP, skin temp and core temp was highly correlated with physiological-state category. Pearson correlation analysis also revealed significant correlation between cardiovascular and thermal parameters, especially blood-pressure and temperature-related parameters with systolic and diastolic blood pressure. These results show that the various physiological traits have a close connection to each other and are more informative as a group than in isolation. None of the separate independent factors were statistically significant and consistent in multinomial logistic regression, indicating that the physiological states are better described by the combination of response patterns. The results overall suggest the potential benefits of integrated cardiovascular and thermal monitoring for physiological-state assessment and as a foundation for future development of wearable and non-invasive monitoring applications.

## References

1. Koul, S., Janani, L., Mir, M. S., Bashir, S., & Ahmad, S. T. (2026). Multimodal Framework for Truck Driver Vigilance and Driving Behavior Classification Using Physiological, Psychological, and Telemetry Data in Naturalistic Driving Conditions. Journal of The Institution of Engineers (India): Series A, 107(2), 323-344.
2. Fonda, H., Irawan, Y., Melyanti, R., Wahyuni, R., & Muhaimin, A. (2024). A comprehensive stacking ensemble approach for stress level classification in higher education. Journal of Applied Data Sciences, 5(4), 1701-1714.
3. Schmidt, P., Reiss, A., Dürichen, R., & Van Laerhoven, K. (2019). Wearable-based affect recognition—A review. Sensors, 19(19), 4079.
4. Bhavani, T., VamseeKrishna, P., Chakraborty, C., & Dwivedi, P. (2022). Stress classification and vital signs forecasting for IoT-health monitoring. IEEE/ACM Transactions on Computational Biology and Bioinformatics, 21(4), 652-659.
5. Gioia, F., Greco, A., Callara, A. L., & Scilingo, E. P. (2022). Towards a contactless stress classification using thermal imaging. Sensors, 22(3), 976.
6. Wang, Z., Yu, Z., Zhao, B., Guo, B., Chen, C., & Yu, Z. (2020). Emotionsense: An adaptive emotion recognition system based on wearable smart devices. ACM Transactions on Computing for Healthcare, 1(4), 1-17.
7. Li, W., Chen, J., & Lan, F. (2022). Human thermal sensation algorithm modelization via physiological thermoregulatory responses based on dynamic thermal environment tests on males. Computer Methods and Programs in Biomedicine, 227, 107198.

8. Romine, W. L., Schroeder, N. L., Graft, J., Yang, F., Sadeghi, R., Zabihimayvan, M., ... & Banerjee, T. (2020). Using machine learning to train a wearable device for measuring students' cognitive load during problem-solving activities based on electrodermal activity, body temperature, and heart rate: development of a cognitive load tracker for both personal and classroom use. Sensors, 20(17), 4833.
9. Mahmud, F., Quamruzzaman, M., Sanka, A. I., Cheung, R. C., & Chowdhury, M. H. (2026). Interpretable machine learning-based real-time sepsis diagnosis. Scientific Reports, 16(1), 6702.
10. Jegan, R., & Nimi, W. S. (2024). On the development of low power wearable devices for assessment of physiological vital parameters: a systematic review. Journal of Public Health, 32(7), 1093-1108.
11. Sahoh, B., Wongsontham, F., Tipsavak, A., Chaithong, P., Kliangkhlao, M., Efendi, M. A., ... & Punsawad, Y. (2026). Deep learning-based comparative evaluation of EEG, HRV, and EDA biomarkers for personal thermal comfort prediction. Biomedical Signal Processing and Control, 113, 108972.
12. Chaudhuri, T., Soh, Y. C., Li, H., & Xie, L. (2020). Machine learning driven personal comfort prediction by wearable sensing of pulse rate and skin temperature. Building and Environment, 170, 106615.
13. Chen, C. H., Lai, F., Chen, Y. L., & Guo, Y. L. (2025). Effects of Heat Adaptation Behaviors on Resting Heart Rate Response to Summer Temperatures in Older Adults: Wearable Device Panel Study. JMIR mHealth and uHealth, 13, e67721.
14. Rodrigues, M. C. J., Postolache, O., & Cercas, F. (2022). Unobtrusive cardio-respiratory assessment for different indoor environmental conditions. IEEE Sensors Journal, 22(23), 23243-23257.
15. Lu, E., Le, T. D., Jouvet, P., & Noumeir, R. (2025). Heart rate and body temperature relationship in children admitted to PICU: A machine learning approach. IEEE Transactions on Biomedical Engineering, 72(8), 2352-2365.
16. Ho, T. F., Tsai, H. H., Chuang, C. C., Lee, D., Huang, X. W., Chen, H., ... & Li, Y. H. (2024). Thermal comfort model established by using machine learning strategies based on physiological parameters in hot and cold environments. Indoor Air, 2024(1), 9427822.
17. Gouverneur, P., Li, F., Adamczyk, W. M., Szikszay, T. M., Luedtke, K., & Grzegorzek, M. (2021). Comparison of feature extraction methods for physiological signals for heat-based pain recognition. Sensors, 21(14), 4838.
18. Li, K., Liu, F., Luo, Y., & Khoso, M. A. (2025). Non-Invasive multivariate prediction of human thermal comfort based on facial temperatures and thermal adaptive action recognition. Energies, 18(9), 2332.
19. Arsalan, A., Majid, M., Nizami, I. F., Manzoor, W., Anwar, S. M., & Ryu, J. (2022). Human stress assessment: A comprehensive review of methods using wearable sensors and non-wearable techniques. arXiv preprint arXiv:2202.03033.
20. Cardone, D., & Merla, A. (2017). New frontiers for applications of thermal infrared imaging devices: Computational psychophysiology in the neurosciences. Sensors, 17(5), 1042.
21. Olyanasab, A., & Annabestani, M. (2024). Leveraging machine learning for personalized wearable biomedical devices: a review. Journal of personalized medicine, 14(2), 203.
22. Tai, Y., Obayashi, K., Okumura, K., Yamagami, Y., & Saeki, K. (2024). Blood pressure, pulse rate, and skin temperature during hot-water bathing in real-world settings among community-dwelling older adults: the HEIJO-KYO Study. Environmental Health and Preventive Medicine, 29, 12-12.
23. Šalkevicius, J., Damaševičius, R., Maskeliunas, R., & Laukienė, I. (2019). Anxiety level recognition for virtual reality therapy system using physiological signals. Electronics, 8(9), 1039.
24. Lee, J. T., Lee, P. F., & Pua, C. H. (2025). Physiological signal synthesis and classification: Assessing entropy change and other physiological signals [Data set]. Mendeley Data, Version 1. https://doi.org/10.17632/r43w3xkzyh.1