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Enhancing the Security of Heart Rate Variability Analysis in Athletes via Two-Factor Authentication

Miroslav Dechev[1*], Yoan-Aleksandar Tsanev[2], Evgeniya Gospodinova[3] & Penio Lebamovski[4]
[1] *Institute of Robotics, Bulgarian Academy of Sciences, Sofia, Bulgaria. Email: miroslav.dechev@gmail.com*
[2] *Technical University, Varna, Bulgaria. Email: joan.al2001@gmail.com;*
[3] *Institute of Robotics, Bulgarian Academy of Sciences, Sofia, Bulgaria. Email: jenigospodinova@abv.bg*
[4] *Institute of Robotics, Bulgarian Academy of Sciences, Sofia, Bulgaria. Email: p.lebamovski@abv.bg*
**Corresponding Author: miroslav.dechev@gmail.com*

Abstract: This paper presents an innovative two-factor authentication (2FA) algorithm designed to protect sensitive biomedical data obtained from heart rate variability (HRV) analysis in athletes. HRV is a non-invasive marker reflecting the balance of the autonomic nervous system and is influenced not only by physical exertion but also by environmental factors such as air quality, climate conditions, and overall lifestyle. The study included 20 athletes examined before, immediately, and 1 hour after training, using electrocardiogram recordings analyzed through linear (time and frequency) and nonlinear (Poincaré) methods. The observed changes in HRV parameters illustrate physiological adaptation to exertion and recovery, which is essential for maintaining sustainable health and preventing overtraining. The innovative aspect of the work lies in its combined approach: secure data protection integrated with advanced physiological monitoring. Graphical visualization of results facilitates personalized training programs, while the developed 2FA algorithm ensures data integrity and confidentiality. Such solutions can be incorporated into intelligent systems for sports medicine and population health monitoring, contributing to sustainable health management in the context of environmental and social challenges.
Keywords: Athletes, Frequency-Domain Analysis, Heart Rate Variability (HRV), Poincarè plot, Time-Domain Analysis, Two-factor Authentication (2FA).

1. INTRODUCTION

Physical exertion and intensive training are integral parts of athletes' daily lives. While physical activity is beneficial for health and sports performance, it must be properly managed. Excessive exertion can lead to physiological stress with serious impacts on cardiac function and overall health. These risks are further influenced by environmental conditions such as air quality, climate, and lifestyle factors, which together shape the adaptive capacity of the human body. In this context, maintaining sustainable cardiovascular health is essential not only for athletes but also for populations exposed to environmental and occupational stressors.

The electrocardiogram (ECG) is a widely recognized non-invasive method for monitoring cardiac activity, enabling the detection of physiological stress and the evaluation of heart rhythm and conduction. One of the key indicators derived from ECG analysis is heart rate variability (HRV), which reflects fluctuations in the intervals between heartbeats and serves as a sensitive marker of autonomic nervous system function. Higher HRV is typically associated with good adaptation and resilience to stress, while reduced HRV can indicate fatigue, overtraining, or increased cardiovascular risk. Importantly, HRV is not only shaped by physical training but also by environmental stressors, making it a valuable tool for integrative health monitoring in the context of environmental influences.

The analysis of HRV in athletes provides critical insights into training adaptation, recovery, and the prevention of overtraining, while also offering a model for studying the interaction between environmental factors and human physiology. At the same time, the growing use of sensitive biomedical data introduces challenges related to information security. Ensuring the confidentiality and authenticity of such data is essential for sustainable health management systems. Two-factor authentication (2FA) algorithms and cryptographic methods can provide reliable protection for HRV data during collection, storage, and transmission.

This article focuses on the development of a novel 2FA algorithm specifically designed to protect HRV-related data in athletes. By combining a password with a one-time code, the algorithm significantly increases the security of cardiological data, preventing unauthorized access and ensuring authenticity. The study presents experimental HRV data from 20 athletes measured before, immediately after, and one hour after training, using linear (time- and frequency-domain) and nonlinear (Poincaré) methods. The results illustrate physiological adaptation to physical exertion and recovery, and their integration with secure data protection methods highlights the potential of intelligent health monitoring systems Such approaches can support both personalized training management and broader strategies for sustainable health in the face of environmental and social challenges.

2. METHODS AND DATA

A. Two-Factor Authentication Algorithm

In today's digital environment, where password theft and security breaches are common, two-factor authentication provides an additional layer of protection that significantly reduces the risk of unauthorized access to user accounts. Two-factor authentication is an identity verification method that requires the user to provide two independent factors to confirm that they are the owner of the account. This significantly increases security compared to simply entering a password. The main steps of the algorithm are [7]:

Step 1: Entering username and password - The user enters their username and password into the system. The server checks whether the entered password matches the stored password.

Step 2: Generate and send a second factor – If the first step is successful, the system generates a second authentication factor, which is a code sent via SMS.

Step 3: The user enters the received code.

Step 4: Second factor verification – The system validates the second factor by checking if the code is valid for the current time interval.

Step 5: System Access - If the second factor is validated successfully, the user is granted access to the account. If unsuccessful, access is denied and a retry may be required.

B. Methods for Analysing HRV and their Relationship with the Stress Index

Methods for analysing HRV include time, frequency, and nonlinear approaches [8-13]. These approaches provide valuable information about the adaptive capabilities of the human body in response to physical and mental stress. Changes in HRV often serve as an indicator of the body's response to stressful stimuli, with reduced HRV usually associated with increased stress levels and limited recovery capacity.

The stress index can be used to quantitatively assess the current state of stress. On this basis, training loads in athletes can be optimized. In addition, the index is useful for assessing the psychophysiological state of patients or for monitoring chronic stress in workers in stressful environments. When measured regularly, the stress index helps to identify trends related to fatigue or overtraining and can serve as a basis for adjustments in the training process [8].

Time-Domain Analysis Includes the Following Metrics [8,14]:

1) *SDNN (standard deviation of all normal RR intervals)* – this metric measures the overall heart rate variability, reflecting both short-term and long-term components of variability. SDNN is related to autonomic nervous system (ANS) function and is used as a general marker of cardiovascular adaptation and stress;
2) *RMSSD (root mean square difference of the squares of the differences between adjacent RR intervals).* This parameter is particularly sensitive to changes in parasympathetic activity. RMSSD is used to assess momentary adaptation responses and is suitable for analysis of short-term recordings;
3) *pNN50%* is one of the temporal metrics for HRV analysis and represents the percentage of consecutive normal RR intervals that differ by more than 50 ms. This metric is closely related to parasympathetic activity and is an indicator of short-term heart rate variability.
4) *HRVti (Heart Rate Variability Triangular Index)* – this index is calculated as the ratio of the total number of NN intervals to the highest value of the histogram of their frequencies. HRVti is an indicator of global HRV and gives an idea of the state of the cardiovascular system;
5) *TINN (Triangular Interpolation of NN Intervals)* – represents the width of the base of the triangle created by interpolation of NN intervals. TINN provides information about the distribution and homogeneity of intervals, being correlated with the total HRV;
6) *Stress Index (SI)* and HRV are closely related, since both parameters reflect the state of the autonomic nervous system and its balance between sympathetic and parasympathetic activity. The Baevsky’s stress index (SI) is computed according to the formula [15]:

$$SI = AMo/2 * Mo * \Delta RR \quad (1)$$

Where:

- AMo: Mode (the most frequent value of RR intervals as a percentage of the total number);
- ΔRR: Range of RR interval variability. A low ΔRR value leads to high SI and reduced HRV, which is a sign of stress;

- **Mo**: The average value of the mode in ms.

7) *The SDNN/RMSSD ratio* can be considered as a marker of the balance between the sympathetic and parasympathetic nervous systems, making it indirectly related to stress. A high value of the SDNN/RMSSD ratio can be interpreted as a dominance of sympathetic activity over parasympathetic activity, which is characteristic of stressful conditions or increased physiological load. A low ratio can indicate balance or parasympathetic dominance, which is associated with lower levels of stress. The lack of standardization and accepted reference values for this parameter limits its universal applicability as an independent indicator for assessing stress, requiring its interpretation to be carried out in the context of other physiological data.

Frequency-domain analysis uses the Fast Fourier Transform (FFT) for spectral analysis. This approach allows the separation of the HRV signal into the following frequency components [8,16,17]:

1) *The low-frequency component (LF)* is usually defined in the range of 0.04–0.15 Hz and is associated with the sympathetic activity of the ANS;
2) *The high-frequency component (HF)* is located in the range of 0.15–0.4 Hz. This parameter is associated with the parasympathetic activity of the ANS and is a sign of relaxation;
3) *The LF/HF ratio* serves to assess the balance between the sympathetic and parasympathetic activity of the ANS. It provides information about the physiological state of the organism, stress levels and the ability to adapt. A high value of this ratio signals sympathetic dominance and stress, while a low value suggests parasympathetic dominance and relaxation. LF/HF can be used as a stress index, but in the context of additional data.

One method for *nonlinear analysis* of HRV is the Poincarè plot [18-20]. It is a geometric method that provides a visual representation of HRV, with each RR interval being compared to the previous one. The diagram constructed with this method shows the scatter of the points. One of the main elements of this method is the identity line: This is the diagonal of the diagram, where RRn=RRn+1. This line represents the "ideal" case in which there is no variability of the RR intervals. Another element is the ellipse, which shows the distribution of the points in the diagram, with SD1 (Short-term variability) and SD2 (Long-term variability) being the axes of the ellipse, with SD1 being the short axis, which is perpendicular to the identity line, and SD2 being the long axis, which is along the identity line. The parameter SD1 is related to the parasympathetic nervous system, and SD2 to the sympathetic nervous system. The ratio: SD1/SD2 shows the relationship between short-term and long-term heart rate variability. A high value of this parameter indicates dominance of parasympathetic activity, while a low value is an indicator of dominance of the sympathetic nervous system. The stress index can be derived from the ratio SD2/SD1, with a high ratio being associated with increased sympathetic tone and higher stress.

Data: The experimental data (RR intervals) used in the study are were recorded by Holter device for a period of 30 minutes in 20 athletes aged 18±1.2 years, training for wrestling. The training session lasted 60 minutes, and electrocardiographic data were recorded at three key moments:

1) Before training (Group 1);
2) Immediately after training (Group 2);
3) One hour after training (Group 3).

Statistical analysis of the data was performed using the t-test, with the value of the parameter p considered statistically significant at $p < 0.05$.

3. RESULTS

Fig. 1 shows the pseudo code of the 2FA algorithm, according to the algorithm described in the previous section.

Table 1 show the results of the mathematical analysis performed using Time-domain, Frequency-domain and the nonlinear Poincarè plot method.

Fig. 2 illustrates the triangular interpolation of the RR interval histogram, representing their distribution. The width of the histogram's base (representing the triangle's base) before training (Fig. 2A) is greater than that observed after training (Fig. 2B).

```
% User data
storedUsername = 'user123';
storedPasswordHash = 'abc123hashedpassword';
storedPhoneNumber = '+359888123456';
% Step 1: Enter username and password. Password verification
inputUsername = input('Enter username: ', 's');
inputPassword = input('Enter password: ', 's');
```

```
if strcmp(inputUsername, storedUsername) && verifyPasswordHash(inputPassword, storedPasswordHash)
disp('Password verified. Proceeding to second factor authentication.');
% Step 2: Generate and send the second factor
EVG = generateEVG();
disp(['Sending SMS code to ', storedPhoneNumber]);
% Sending SMS (simulation)
sendSMS(storedPhoneNumber, EVG);
% Step 3: Enter the second factor
inputEVG = input('Enter the code received via SMS: ', 's');
Step 4: Verify the second factor
if strcmp(inputEVG, EVG)
disp('Second factor verified. Access granted.');
% Step 5: Access the system
else
disp('Invalid code. Access denied.');
end
else
disp('Invalid username or password. Access denied.');
end
% Password verification function
function Valid = verifyPasswordHash(inputPassword, storedHash)
% Hashing algorithm
hashedInput = simpleHash(inputPassword);
Valid = strcmp(hashedInput, storedHash);
end
% One-time code generation feature
function EVG = generateEVG() %6-digit code
EVG = num2str(randi([100000, 999999]));
end
% SMS sending function
function sendSMS(phoneNumber, message)
fprintf('SMS sent to %s: %s\n', phoneNumber, message);
end
% Hash function
function hash = simpleHash(password)
hash = ['abc123' password];
end
```

Fig. 1 Two-factor authentication algorithm pseudo code.

Table I.

HRV parameters of athletes (wrestlers) determined before training (Group 1), immediately after training (Group 2) and one hour after training (Group 3)

Parameter	**Group 1** n=20 [mean±std]	**Group 2** n=20 [mean±st]	**Group 3** n=20 [mean±std]	**P-value Gr_1/Gr_2**
Time-domain analysis				
Mean RR[ms]	701.3±31	563.45±21	698.9±32	0.0001
SDNN[ms]	59.7±6.01	44.65±10.9	57.81±5.03	0.0001
RMSSD [ms]	60.1±8.63	27.75±8.98	58.31±7.81	0.0001
pNN50 [%]	31.8±4.21	5.3±0.09	29.05±2.21	0.0001
HRVti [-]	12.1±5.03	4.05±1.19	11.91±4.09	0.0001
TINN [ms]	227.9±61.2	133.4±41.1	225.3±59.1	0.0001
SI [-]	0.994±0.69	1.64±1.09	1.08±0.59	0.0341

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Parameter	Group 1 n=20 [mean±std]	Group 2 n=20 [mean±st]	Group 3 n=20 [mean±std]	P-value Gr_1/Gr_2
Frequency-domain analysis				
nLF [nu]	55.48±3.03	75.44±3.23	56.31±2.96	0.0001
nHF [nu]	144.51±7.5	124.51±6.41	146.23±6.1	0.0001
LF/HF [-]	0.38±0.09	0.60±0.16	0.38±0.19	0.0001
Nonlinear analysis (Poincarè plot)				
SD1 [ms]	35.47±6.12	16.02±4.31	31.01±5.67	0.0001
SD2 [ms]	94.83±11.3	58.44±9.89	89.91±11.6	0.0001
SD2/SD1 [-]	2.87±0.39	3.25±0.41	0.34±0.10	0.0070

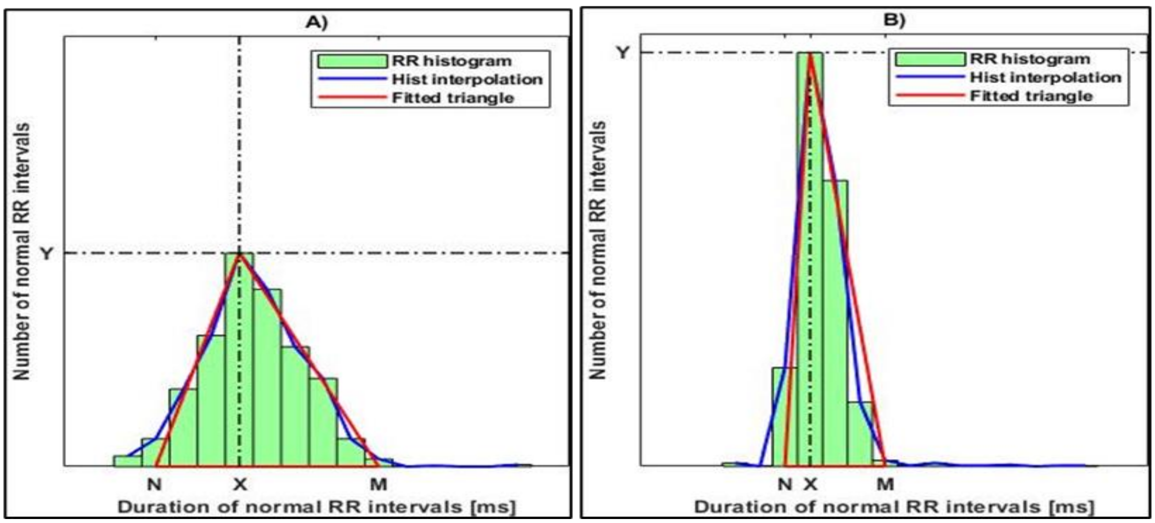

Fig. 2 Triangular interpolation of RR interval histogram of wrestling athletes: (A) before training; (B) after training.

The graph shown in Fig. 3A reflects the athlete's resting state, in which the parasympathetic nervous system dominates. The parameters SD1 and SD2 are significantly larger, with a higher value of SD1 being an indicator of stronger parasympathetic activity and relaxation. The larger ellipse indicates a higher HRV, which is characteristic of a good functional state of the Autonomic Nervous System. In Fig. 3B, the graph represents the state of the athlete after training. There is a clear decrease in SD1, which is an indicator of suppression of parasympathetic activity due to physical exertion. SD2 is also slightly reduced, reflecting a decrease in overall HRV. The reduced size and narrower shape of the ellipse indicate a normal physiological response of sympathetic dominance, which is necessary for the body to adapt to physical stress.

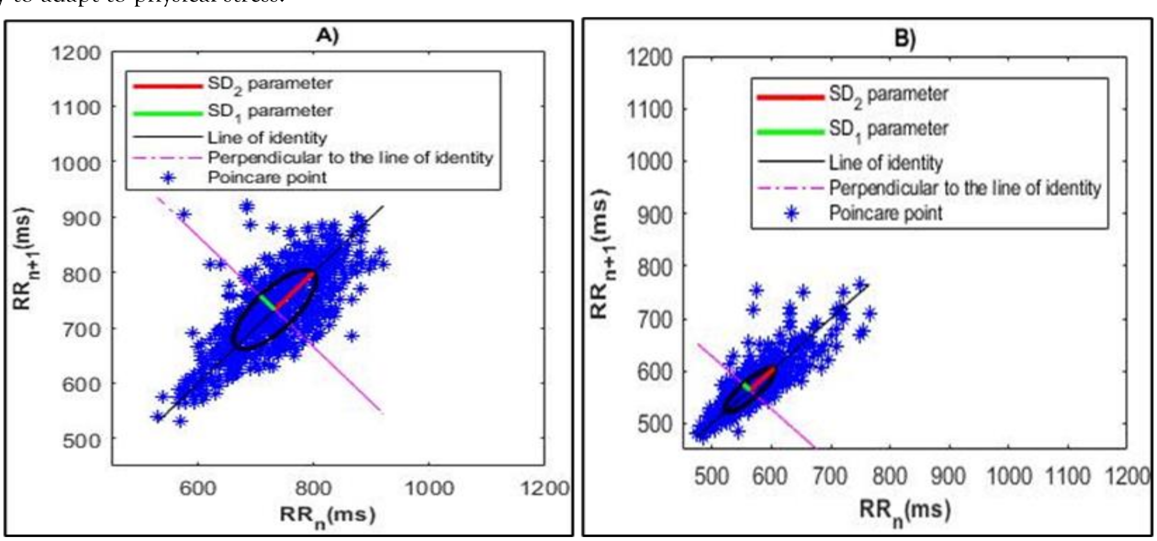

Fig. 3 Poincarè plot of athletes practicing wrestling: (A) before training; (B) after training.

4. DISCUSSION

The developed algorithm for two-factor authentication using SMS as the second factor significantly increases security compared to standard password authentication. The advantage of this method is its easy implementation and wide applicability, since it does not require additional hardware. However, SMS-based authentication has certain vulnerabilities related to message interception and dependence on the mobile network. Therefore, in systems with higher security requirements, it is advisable to use more robust methods, such as mobile applications for generating codes or hardware authentication devices, which will provide a higher level of protection compared to SMS-based methods. Despite its limitations, the described algorithm remains suitable for systems with a medium level of risk, where the balance between security and user convenience is important. Analysis of heart rate variability provides valuable information about the autonomic regulation of the cardiovascular system and adaptation mechanisms in the body of athletes. The present study focuses on the relationship between the values of HRV indices in the time and frequency domains, as well as the nonlinear Poincarè plot method, on the one hand, and the stress induced by sports training in wrestlers, on the other. Based on the obtained results, the following conclusions can be made:

1) Lower values of the SDNN and RMSSD parameters after exercise are an indicator of a temporary decrease in parasympathetic activity and/or activation of the sympathetic nervous system. After physical activity, the body responds by increasing heart rate and decreasing HRV, which is a normal response to the stressful stimulus of exercise. These values may remain low for some time after exercise until the body begins the recovery process. As the recovery process progresses, HRV usually increase, signalling a predominance of parasympathetic activity. Lower values of these parameters may be more pronounced after intense or prolonged exercise, as they cause greater activation of the sympathetic nervous system.
2) Under stress, the heart rate becomes more uniform and the NN intervals are less varied, which leads to a narrower distribution in the histogram (Fig. 2B) and, accordingly, a lower HRVti value. A low HRVti value may be an indicator of increased tension, overload, or insufficient recovery. A prolonged decrease in HRVti under chronic stress may signal a risk of cardiovascular disease, reduced resistance to stressors, and poor general health. HRVti is useful in assessing the general functional state of the autonomic nervous system, as its decrease under stress conditions indicates a disturbed balance between the sympathetic and parasympathetic nervous systems. Often, the use of the HRVti parameter in HRV analysis is considered together with other HRV indicators (e.g., RMSSD, SDNN) to obtain a complete picture of the body's response to stress.
3) Under stress caused by physical exertion, the value of the TINN parameter also decreases. This is due to increased sympathetic activity and decreased parasympathetic activity, which leads to a narrower distribution of the NN intervals. The narrow range of the NN intervals indicates that the heart rate becomes more uniform, characteristic of a stressful state. The decrease in TINN under stress caused by sports training is a sign of temporarily increased sympathetic activity. However, it is important that the TINN values normalize after a certain period of rest. If this does not happen, it is advisable to review the training regimen or pay attention to the factors hindering recovery. The results of our study show that the values of this parameter normalize within 1 hour after the end of the training. This demonstrates that the training program of the athletes is appropriate. Similar results were reported in a publication [8].
4) The pNN50% parameter is a sensitive indicator of stress and recovery from a stressful situation. A decrease in this parameter is usually associated with increased stress, while an increase is a sign of effective recovery from training and low stress levels. Tracking pNN50% is particularly useful for assessing training balance and monitoring the body's adaptation to physical exertion.
5) The stress index and HRV are interrelated indicators that determine the state of autonomic regulation. While HRV provides a general assessment of the flexibility of cardiac regulation, SI provides a focused assessment of sympathetic activity. Using them together gives a more complete picture of the stress and adaptive capabilities of the athlete's body.
6) Based on the results obtained from the spectral analysis of HRV at rest, presented in Table I, it is established that the LF parameter is moderately active with a value of 55.48 [nu], while HF has a highly expressed value of 144.51 [nu]. The LF/HF ratio is 1.33, which is an indicator of balanced activity of the ANS at rest. Immediately after training, the LF value increases, HF decreases, and the LF/HF ratio also increases. These changes reflect the dominance of sympathetic activity in the ANS in response to physical exertion. One hour after training, the values of LF, HF, LF/HF gradually return to their initial values, which indicates restoration of balance in the Autonomic Nervous System.

7) The graphs obtained by the Poincarè plot (Fig. 3) have a comet-like shape, with a pointed lower part that gradually widens towards the top. This shape is characteristic of cardiacally healthy individuals with high HRV, in accordance with data from previous publications [8,17]. The points in the Poincarè plot are symmetrical about the identity line, which is an indicator of the absence of rhythm disturbances. After training (Fig. 3B), the athlete's graph becomes compressed, which reflects the more even intervals between heartbeats, as a result of physical exertion, which leads to a decrease in HRV.
8) The results of the quantitative analysis of the parameters determined by the Poincarè plot can be used as an additional tool for assessing HRV. The values of the parameters SD1 and SD2 are higher at rest, which is an indicator of a higher HRV of the athletes before training. During training, the values of these two parameters decrease, reflecting the physical load and the associated temporary decrease in HRV. In addition, the higher value of the ratio SD1/SD2 at rest confirms the higher HRV before training. After the cessation of the stress factor, SD1, SD2 and the ratio SD1/SD2 should return to normal values characteristic of rest. If this does not happen, there may be a problem with adaptation or chronic overload.
9) Importantly, the findings also emphasize that HRV is not only a marker of training load but also of environmental and social stressors, including air quality, temperature, and lifestyle. In this sense, the developed approach integrates secure data protection with physiological monitoring, making it applicable not only in sports medicine but also in broader contexts of public health and environmental health research. Ensuring confidentiality and authenticity of sensitive biomedical data supports sustainable health management systems that can be extended to monitor population well-being under diverse environmental challenges.

5. CONCLUSIONS

In this study, a two-factor authentication algorithm using SMS as the second factor for verifying user identity was presented. The algorithm demonstrates effectiveness in increasing security compared to traditional identification methods, while maintaining an easy and user-friendly implementation. Nevertheless, the identified vulnerabilities related to SMS communications highlight the importance of implementing more reliable mechanisms in critical systems. Future work will focus on developing advanced multi-factor authentication (MFA) methods to achieve an optimal balance between security and user convenience.

The integration of HRV analysis methods into sports practice enables detailed monitoring of the body's adaptive capabilities. Linear methods provide insight into the instantaneous state of heart rate, while nonlinear methods capture long-term variability and stability. Their combination allows the creation of more accurate algorithms for individualizing training regimens, optimizing athletic performance, and reducing the risk of overtraining and injury.

The innovation of this study lies in its combined approach: integrating advanced HRV analysis with secure data protection. Beyond sports practice, this approach supports the principles of preventive medicine and contributes to sustainable health by enabling continuous monitoring of physical activities in everyday life.

By emphasizing the interaction between physical exertion, environmental and social stressors, and physiological adaptation, HRV analysis becomes a powerful tool for understanding the dynamic relationship between humans and their environment. The proposed framework can be applied in intelligent health and environmental monitoring systems, supporting population well-being and resilience in the face of modern environmental challenges.

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