Article

Not peer-reviewed version

Metabolic and Fitness Correlates of Heart Rate Variability in Middle-Aged Endurance Athletes: A Pilot Study Using Continuous Glucose Monitoring and Machine Learning

Spyridon Patsialos * and Yiannis Koumpouros

Posted Date: 4 February 2026

doi: 10.20944/preprints202602.0332.v1

Keywords: heart rate variability; continuous glucose monitoring; wearable sensors; machine learning; autonomic nervous system; endurance athletes; metabolic variability

Article

Metabolic and Fitness Correlates of Heart Rate Variability in Middle-Aged Endurance Athletes: A Pilot Study Using Continuous Glucose Monitoring and Machine Learning

Spyridon Patsialos [1] and Yiannis Koumpouros [2]

[1] Digital Innovation in Public Health Research Lab, Department of Public and Community Health, University of West Attica, Athens, Greece

[2] Digital Innovation in Public Health Research Lab, Department of Public and Community Health, University of West Attica, Athens, Greece

* Correspondence: spatsialos@uniwa.gr

Highlights

This research contributes to the growing field of digital health analytics, demonstrating the potential of Continuous Glucose Monitoring (CGM) and Heart Rate Variability (HRV) tracking for personalized training and health management. By combining AI-driven predictive modeling, athletes and healthcare professionals can gain valuable insights into performance optimization, overtraining prevention, and overall cardiovascular health.

Abstract

Background: HRV is a key biomarker of autonomic nervous system function and cardiovascular health. Emerging evidence suggests that metabolic regulation, particularly glucose variability, may influence autonomic balance even in non-diabetic populations. With the increasing availability of CGM and wearable sensors, the integration of metabolic and cardiovascular signals enables novel data-driven approaches for personalized health monitoring. **Objectives**: This pilot study aimed to investigate the associations between glucose dynamics, fitness indicators, and HRV in middle-aged amateur endurance athletes, and to evaluate the feasibility of predicting HRV using machine-learning models based on CGM and wearable-derived features. **Methods**: Ten male endurance athletes (age 39–50 years) were monitored over a two-month period using CGM devices and advanced smartwatches. Daily metrics included average glucose, glucose standard deviation and coefficient of variation, resting heart rate (RHR), nocturnal HRV (RMSSD), blood oxygen saturation (SpO_2), and estimated VO_2max. Anthropometric and biochemical markers (BMI, fat mass, skinfolds, HbA1c, ApoB, vitamin D) were also collected. Random Forest, XGBoost, and LightGBM regression models were trained to predict HRV. Model performance was evaluated using cross-validated R^2 (R^2 ranged from 0.12 to 0.28) and normalized mean absolute error (nMAE). **Results**: Correlation analysis revealed that elevated ApoB, increased fat mass, and higher RHR were strongly associated with lower HRV. Glucose variability showed weaker associations in this cohort. Machine-learning models demonstrated limited predictive accuracy for HRV ($R^2 < 0.30$ across models), suggesting that while physiological links exist, the selected features alone are insufficient to fully explain HRV variability in a pilot cohort. **Conclusions**: In middle-aged endurance athletes, glucose regulation and cardiovascular fitness markers show meaningful associations with autonomic function, but the feasibility of accurately predicting HRV from CGM-derived metrics remains limited in this pilot dataset. These findings support the physiological link between metabolic stability and autonomic balance, while highlighting the need for larger longitudinal datasets and time-series modeling to capture the complex dynamics between glucose fluctuations and cardiac autonomic regulation.

Keywords: heart rate variability; continuous glucose monitoring; wearable sensors; machine learning; autonomic nervous system; endurance athletes; metabolic variability

1. Introduction

Heart Rate Variability (HRV) refers to the variation in time intervals between heartbeats and it is recognized as a crucial physiological marker reflecting autonomic nervous system function, cardiovascular health, and endurance performance. It is used to analyze the Autonomic Nervous System (ANS), a control system used to modulate the body's unconscious action such as cardiac function, respiration, digestion, blood pressure, urination, and dilation/constriction of the pupil. High heart rate variability (HRV) indicates good health, while reduced HRV is associated with increased morbidity and stress. Low HRV is linked to anxiety, depression, burnout, and even cardiovascular issues [2–4].

Furthermore, Glycated hemoglobin (HbA1C) is a marker of long-term blood glucose levels. The relationship between HbA1C and HRV in healthy populations can provide insights into early metabolic disturbances and cardiovascular health [1]. It has been thoroughly studied that higher HbA1C levels are associated with autonomic imbalance [26]. Monitoring HbA1C levels in conjunction with HRV could provide valuable insights into the early stages of metabolic and cardiovascular health deterioration.

Despite the fact that athletes try to keep up with their carbohydrates intake in order to feel more energized during the day, elevated average glucose levels are associated with reduced HRV, indicating impaired cardiac autonomic function. This relationship is observed across various conditions, including diabetes and glucose intolerance. HRV is inversely related to plasma glucose levels. Higher glucose levels, whether in diabetes or impaired fasting glucose, are linked to reduced HRV parameters such as SDNN, LF, and HF power [6]. Rapid changes in glucose levels, such as those observed during glucose tolerance tests, can significantly reduce HRV, particularly during rapid glucose rises [7]. This suggests that not only average glucose levels but also fluctuations can impact cardiac autonomic function. In healthy individuals, experimentally induced glucose intolerance through glucose infusion decreases HRV, highlighting the potential early impact of glucose dysregulation on cardiac autonomic activity [8]. Even in individuals without diabetes, higher fasting glucose and insulin resistance are associated with lower HRV, particularly in men and those with abdominal adiposity [10].

A technology field that allows for real-time or near-real-time tracking of glucose levels, primarily used in diabetes management Continuous glucose monitoring (CGM). Recent advancements in wearable technology and CGM offer novel avenues for real-time capture and assessment of physiological interactions. CGM systems have evolved rapidly, offering detailed insights into glycemic variability and supporting both patients and clinicians in making informed decisions about therapy and lifestyle adjustments [9].

This research was motivated by the potential to understand how glucose levels and fitness indicators influence HRV in middle-aged amateur endurance athletes. The study sought to contribute to personalized training strategies and inform clinical practice by identifying predictive relationships between these factors. The primary objective was to use machine learning (ML) techniques to discover the correlation and develop models capable of predicting HRV fluctuations based on glucose levels and fitness markers in this specific population. This pioneering approach aims to provide actionable insights for athletes seeking to optimize performance, recovery, and cardiovascular health. The research uniquely integrates AI, physiology, and nutrition, applying it to amateur athletes often underrepresented in sports science research.

Prior research has separately addressed the implications of glucose levels and fitness metrics on HRV, but few studies have integrated these dimensions, particularly using real-world continuous data.

 doi:10.20944/preprints202602.0332.v1

This work is inspired by emerging evidence linking excessive endurance exercise and poor carbohydrate metabolism to reduced HRV, which can reflect heightened physiological stress and cardiovascular strain. The study's goal was to analyze whether non-invasive, daily monitoring of glucose and fitness markers could help endurance athletes optimize training and recovery, and potentially mitigate cardiovascular risk. Therefore, this study was designed as a hypothesis-generating pilot investigation.

2. Materials and Methods

This observational study followed ten (10) amateur endurance athletes (aged 39-50), with at least 8 years of consistent endurance training, for a period of two months. The study adhered to ethical guidelines, with informed consent obtained from all participants. Each participant was equipped with a CGM device (intelliGO free) for continuous glucose monitoring and high-end smartwatches (Garmin 6 or 7 and WHOOP 4.0) for measuring HRV, resting heart rate, and blood oxygen saturation. Participants were equipped with CGM devices that provided real-time glucose readings throughout the day and night, enabling detailed analysis of glucose fluctuations in relation to physical activity and stress levels. The CGM system used in this study consisted of two main components:

- Transmitter: A small Bluetooth-enabled device that sent real-time glucose readings to a smartphone application.
- Sensors/Readers: Adhesive sensors attached to the abdominal area to measure interstitial glucose levels.

Each sensor was replaced every 14 days. The CGM system recorded and transmitted glucose values every 3 minutes. To ensure accuracy, participants were trained to calibrate their CGM sensors using blood glucose meters. Participants' glucose data were uploaded to their smartphones via Bluetooth protocol. Software provided by the manufacturer was used to download and export CGM data to Excel datafiles (this is anyway a key advantage of CGMs, the fact that they allow remote monitoring capability).

The participants also wore their devices capable of measuring RHR, SpO_2, VO_2 max, and HRV. Metrics were collected as described in the table below:

Table 1. The variables used for the data collection.

Category	Feature	Frequency
Glucose Metrics	AVG Glucose, SD, CV	Daily
Heart Metrics	HRV, RHR	Overnight, daily
	VO2 max	Weekly
Oxygen saturation	SpO_2	Daily average
Anthropometric Data	BMI Fat Mass % Sum of 8 skinfolds	Once
Blood Biomarkers	HbA1C ApoB Vitamin D3	Once

 doi:10.20944/preprints202602.0332.v1

In this study, Anaconda with Jupyter Notebook was used as the primary environment for conducting Exploratory Data Analysis (EDA), preprocessing, feature engineering, and implementing machine learning models. Data preprocessing techniques used to ensure data integrity. Key libraries such as Pandas, Matplotlib, Seaborn, Scikit-Learn used for data analysis and visualization. Finally, the machine learning models (Random Forest Regressor, XGBoost Regressor, LightGBM Regressor) applied for HRV prediction and the evaluation metrics (Mean Absolute Error, Normalized Mean Absolute Error, R-Squared) used to assess model performance. The processing pipeline followed during this research is illustrated in Figure 3 and described below:

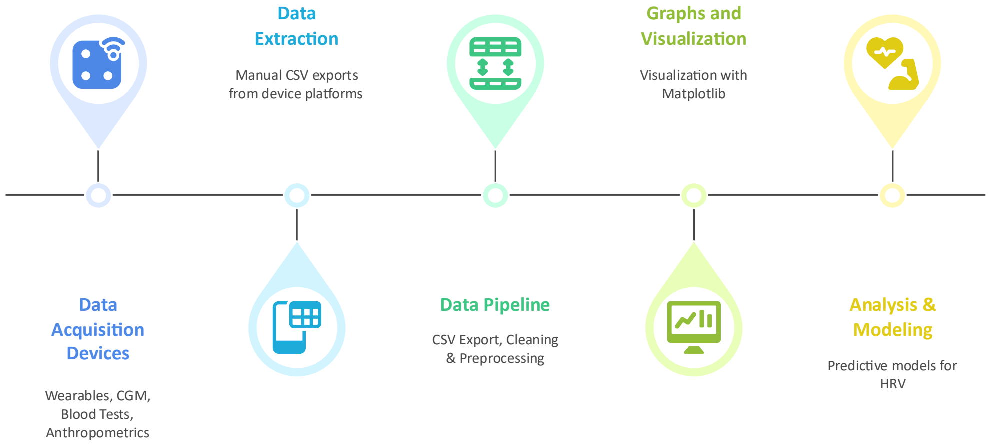

Figure 1: Processing pipeline of the proposed analysis

While the number of participants is small, the study follows a high-density longitudinal design. Data collection spanned 60 consecutive days for each athlete, utilizing Continuous Glucose Monitoring (CGM) devices that recorded measurements every 3 minutes (totaling 480 data points per day per participant). This resulted in a robust dataset consisting of hundreds of observations per subject. To address the risk of overfitting, several rigorous validation techniques were implemented, like personalized modeling, data splitting etc.

The choice of ML (Random Forest and XGBoost) over Multiple Linear Regression was driven by the relationship between glucose levels, fitness indicators, and Heart Rate Variability (HRV), which is inherently complex and non-linear. Linear models often fail to capture these intricate physiological interactions. Also, Tree-based ML algorithms allow for the ranking of feature importance, providing deeper insights into which metabolic and physical factors most significantly impact HRV. Finally ensemble methods like Random Forest are specifically designed to handle high-dimensional data and are more resilient to outliers compared to standard regression models in biological datasets.

The main analytical purpose of ML in this study was to obtain feature importance rankings, generating insight for future larger-scale studies, laying the groundwork for future studies with expanded cohorts.

1. **Data Acquisition Devices:**
- **Wearables:** Garmin Fenix 6 or 7 and WHOOP 4.0
- **CGM Device:** Continuous Glucose Monitor placed on the abdomen.
- **Blood Tests:** Cholesterol, HbA1c, vitD, ApoB
- **Anthropometrics:** BMI, Fat Mass %, Sum of 8 Skinfolds

2. **Data Extraction:**

Performed **manually** via **CSV exports** from respective device platforms or lab reports

3. **Data Pipeline:**
- Manual CSV Export
- Data Cleaning & Preprocessing
- Visualization with Matplotlib

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 4 February 2026 doi:10.20944/preprints202602.0332.v1

4. Analysis & Modeling

- Used in models to predict HRV based on glucose variability and fitness/anthropometric metrics.
- **ML algorithms tested:**
  - Random Forest
  - LightGBM
  - XGBoost
- **Evaluation metrics:**
  - Normalized MAE
  - R^2
- Participants were not limited to passive or resting data acquisition. Instead, they continuously wore CGM devices during both structured training sessions and competitive endurance events. Specifically, data were collected during prolonged aerobic training exceeding one hour, a certified 42-kilometer road marathon, and a high-intensity 4-hour trail race. This approach enabled the capture of dynamic glycemic responses under real-world physiological stress [11].
- The inclusion of these high-demand scenarios enhanced the ecological validity of the dataset and provided critical insight into exercise-induced metabolic fluctuations. As anticipated, significant intra and inter individual glucose variability was observed during prolonged physical exertion [12]. Importantly, this allowed for the investigation of potential associations between acute glycemic excursions and nocturnal autonomic recovery, as reflected in derived HRV metrics recorded via wearables [13].
- Preliminary analyses suggest that elevated glycemic variability during endurance activities may influence subsequent parasympathetic modulation during nocturnal recovery periods. These findings support the emerging hypothesis that metabolic stress during exercise interacts with autonomic nervous system activity, potentially affecting recovery quality and cardiovascular homeostasis.All physiological data were synchronized using timestamps. Data points were checked for outliers and corrected where sensor errors occurred. Glucose variability was assessed using both the standard deviation and coefficient of variation.

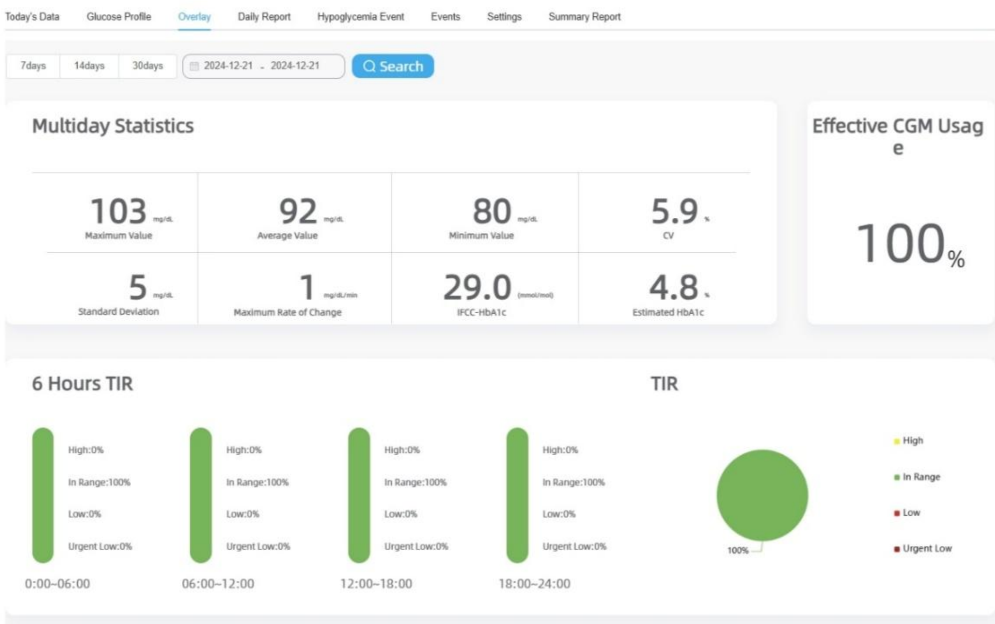

Figure 2: Screenshot from the CGM metrics platform

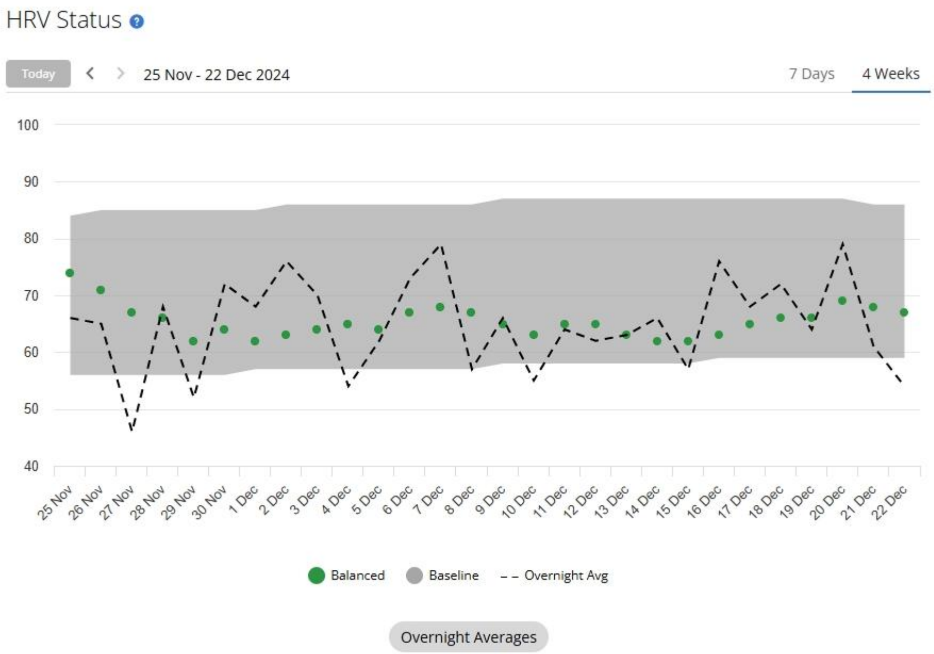

Figure 3. HRV status. Garmin's page for gathering the Overnight Average for HRV.

The Key Libraries and Tools used were:

- Pandas – For data manipulation and numerical computations.
- Matplotlib & Seaborn – For visualization and statistical insights.
- Scikit-Learn – For implementing machine learning models and evaluation metrics.
- XGBoost & LightGBM – For advanced gradient boosting techniques.
- Jupyter Notebook Extensions – For improved productivity and workflow management.
- The workflow followed in Jupyter Notebook involved:
- Data Loading & Preprocessing: Using Pandas to import and clean the dataset.
- Exploratory Data Analysis (EDA): Visualizing feature distributions and correlations.
- Feature Engineering: Creating new variables, scaling, and handling missing values.
- Machine Learning Model Implementation: Training models using Random Forest, XGBoost, and LightGBM.
- Model Evaluation & Optimization: Hyperparameter tuning with GridSearchCV and evaluation using R^2 and MAE.

3. Results

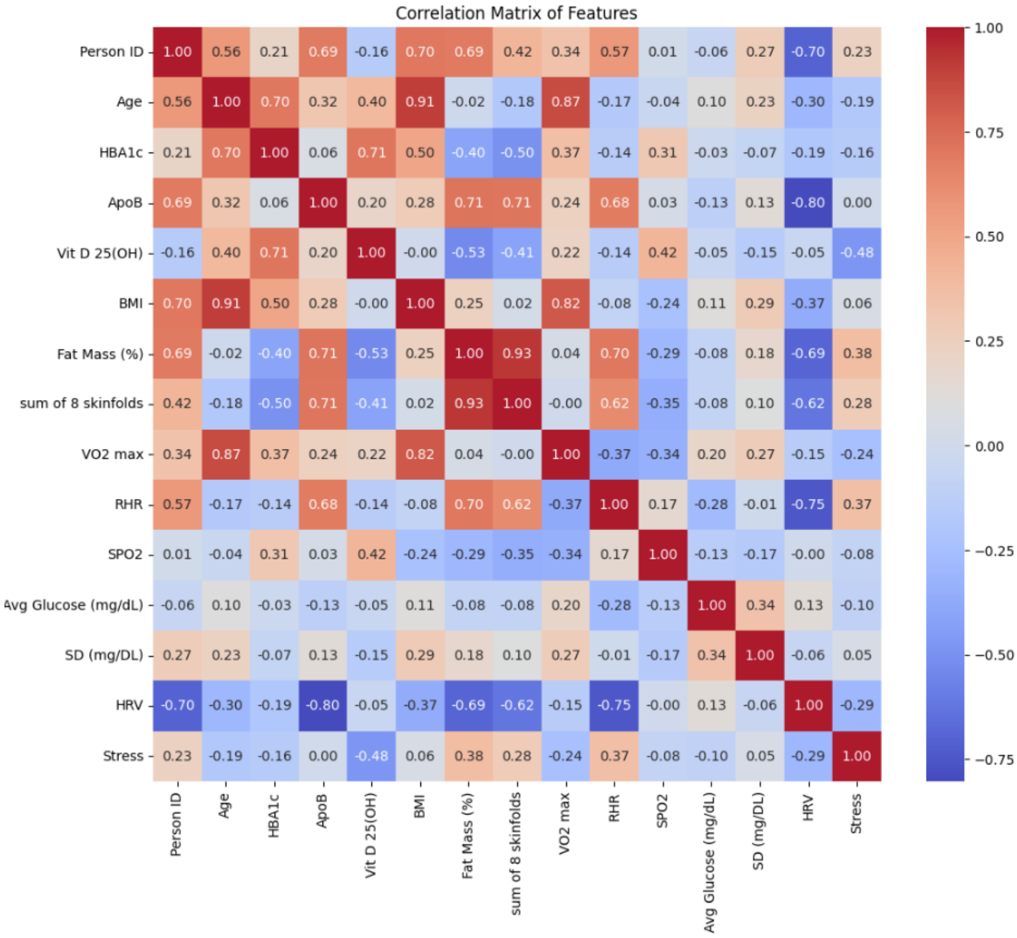

Figure 4. correlation matrix of features.

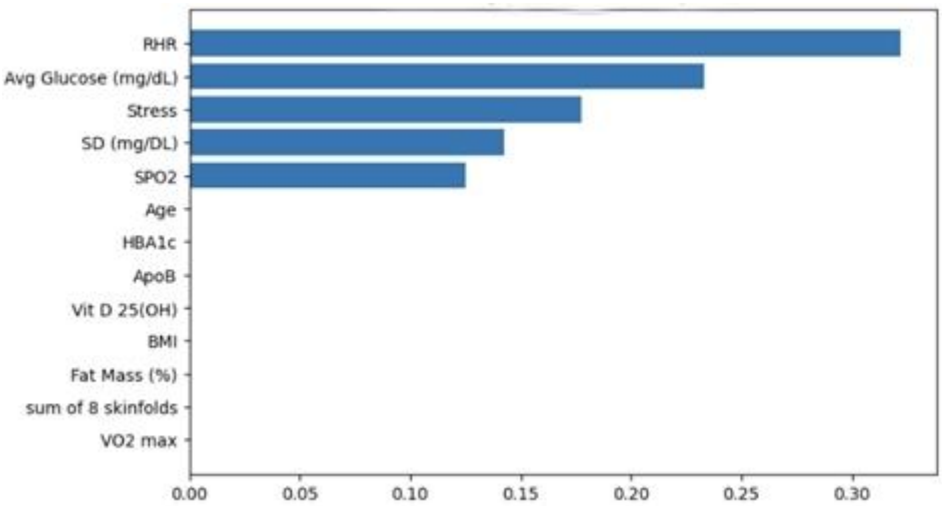

Figure 5. feature importance barplot for one participant.

According to the correlation matrix above and the feature importance barplot, the main observations for HRV and insights for model prediction are the following:

1. ApoB: Higher ApoB (a cardiovascular risk marker) is strongly linked to lower HRV.
2. Fat Mass: Increased fat percentage is associated with lower HRV.

 doi:10.20944/preprints202602.0332.v1

3. RHR: A higher resting heart rate (RHR) is linked to lower HRV, which makes physiological sense.
4. BMI: Suggests that individuals with higher BMI may have lower HRV.
5. Sum of 8 Skinfolds: More subcutaneous fat is associated with lower HRV.
6. Avg Glucose (mg/dL) has a correlation of (0.13) with Stress, meaning there is a weak positive relationship.
7. Stress: Showing a weak negative correlation, meaning that lower HRV is a strong predictor of higher stress.
8. HRV is better predicted by physiological and cardiovascular markers (ApoB, Fat Mass, RHR).

ID	Random Forest MAE	Random Forest R^2	Random Forest MAE (less features)	Random Forest R^2 (less features)	XGBoost MAE	XGBoost R^2	XGBoost (Less Features) MAE	XGBoost (Less Features) R^2	LightGBM MAE	LightGBM R^2
1	7,375	0,316	6,533	0,278	8,897	0,136	6,624	0,081	8,665	0,183
2	4,811	0,12	4,569	0,226	5,742	0,014	5,544	0,05	6	-0,109
3	5,3	-0,196	5,377	-0,295	5,196	-0,16	5,676	-0,617	4,875	-0,015
4	4,153	-0,059	4,57	-0,175	4,417	-0,112	4,174	-0,108	3,872	-0,083
5	2,193	0,104	2,341	-0,018	2,45	0,189	2,964	-0,008	3,1	-0,004
6	1,959	0,607	2,021	-0,457	1,226	0,598	1,697	0,164	1,469	0,3

Figure 6. Model's performance comparison.

4. Discussion

This study examined the predictive capability of various machine learning models for estimating HRV based on physiological and metabolic parameters, including RHR, SpO2, Average Glucose, Glucose Standard Deviation, and Stress. The models evaluated included Random Forest, XGBoost, and LightGBM, with additional experiments on feature selection and dimensionality reduction.

The results indicate that none of the tested models demonstrated strong predictive power for HRV. The consistently low R2 scores suggest that the selected features may not sufficiently capture the variability in HRV, highlighting the need for enhanced feature engineering. Incorporating additional transformations, such as rolling averages, feature interactions, or temporal differences, may improve model performance.

Furthermore, the dataset size appears to be a limiting factor in achieving higher predictive accuracy. Expanding the dataset with data from a larger and more diverse cohort could enhance model generalizability. Future research should prioritize increasing the sample size and considering data collection during periods of lower training intensity, where physiological responses may be more stable. Additionally, monitoring HRV in conditions where external factors such as stress and sleep duration remain relatively constant could provide clearer insights into the relationship between glucose levels and HRV.

5. Conclusions

This study highlights the strong link between glucose regulation and Heart Rate Variability, reinforcing the importance of metabolic efficiency in both cardiovascular function and long-term health. While glucose stability is often discussed in the context of athletic performance, this research shifts the focus toward its role in longevity and overall well-being. Rather than aiming to enhance HRV solely to improve endurance performance, the ultimate goal is to explore how better metabolic control can contribute to autonomic balance, reduced disease risk, and healthier aging.

The observed individual variability in glucose sensitivity suggests that a personalized approach to glucose management is essential, not only for athletes but for the general population as well. By understanding how fluctuations in glucose impact HRV, individuals can adopt lifestyle modifications (such as dietary adjustments, stress management, and optimized sleep) that promote long-term cardiovascular resilience.

While this study provides valuable insights, it also presents certain limitations. The relatively small sample size and the reliance on wearable-derived physiological data may introduce variability in measurement accuracy. Additionally, the study does not establish causal relationships between glucose fluctuations and HRV, emphasizing the need for interventional research to further explore these dynamics. Future studies should focus on real-time monitoring, larger participant pools, and controlled dietary interventions (such as ketogenic or low-glycemic diets) to assess the potential for glucose-targeted strategies in improving autonomic function and longevity.

Furthermore, this research underscores the growing role of wearable technology in preventive healthcare. Integrating real-time metabolic and cardiovascular data into HER systems could empower individuals and healthcare providers to make proactive, data-driven decisions. By leveraging Big Data and AI-driven analytics, future advancements could refine personalized health interventions, particularly for aging populations and individuals at risk of metabolic disorders.

Author Contributions: Conceptualization, S.P. ; methodology, S.P.; Y.K.; writing—original draft preparation, S.P.; writing—review and editing, Y.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study. Written informed consent has been obtained from the participants to publish this paper.

Data Availability Statement: Data gathered for this study are unavailable due to privacy or ethical restrictions.
Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CGM	Continuous Glucose Monitoring
HRV	Hear Rate Variability
ANS	Autonomic Nervous System
ML	Machine Learning
WT	Wearable Technology
SD	Standard Deviation
CV	Coefficient of Variance
RMSSD	Root Mean Square of Successive Differences

References

1. Yu, J., Hussein, A., Mah, L., & Chen, J. (2024). The associations among glycemic control, heart variability, and autonomic brain function in healthy individuals: Age- and sex-related differences. *Neurobiology of Aging*, 142, 41-51. https://doi.org/10.1016/j.neurobiolaging.2024.05.007.
2. Aggarwal, P., Kuppusamy, S., Prakash, P., Subramanian, S., & Fredrick, J. (2024). Is fat-to-lean mass ratio a better predictor of heart variability than body mass index? *Journal of Education and Health Promotion*. Retrieved from https://doi.org/10.4103/jehp.jehp_539_23.
3. Alugubelli, N., Abuissa, H., & Roka, A. (2022). Wearable Devices for Remote Monitoring of Heart Rate and Heart Rate Variability:What We Know and What Is Coming. *Sensors*. Retrieved from https://doi.org/10.3390/s22228903
4. Bauhaus, H., Erdogan, P., Braun, H., & Thevis, M. (2023). Continuous Glucose Monitoring (CGM) in Sports - A Comparison between a CGM Device and Lab-Based Glucose Analyser under Resting and Exercising Conditions in Athletes. *International Journal of Environmental Research and Public Health*. Retrieved from https://doi.org/10.3390/ijerph20156440

5. Bellenger, C., Fuller, J., Thomson, R., Davison, K., Robertson, E., & Buckley, J. (2016). Monitoring Athletic Training Status Through Autonomic Heart Rate Regulation: A Systematic Review and Meta-Analysis. *Sports Medicine*, pp. 1461-1486. Retrieved from https://doi.org/10.1007/s40279-016-0484-2
6. Bourdon, J., Moore, A., Eastman, M., Savage, J., Hazlett, L., Vrana, S., . . . Roberson-Nay, R. (2018). Resting Heart Rate Variability (HRV) in Adolescents and Young Adults from a Genetically-Informed Perspective. *Behavior Genetics*, pp. 386 - 396. Retrieved from https://doi.org/10.1007/s10519-018-9915-1
7. Bowler, A. M., Whitfield, J., Marshall, L., Coffey, V. G., Burke, L. M., & Cox, G. R. (2024, 11 22). The Use of Continuous Glucose Monitors in Sport: Possible Applications and Considerations. *International Journal of Sport Nutrition and Exercise Metabolism*. Retrieved from https://doi.org/10.1123/ijsnem.2022-0139
8. Brink, H., Richards, J. W., & Fetherolf, M. (2017). *Real-World Machine Learning.* Shelter Island, NY: Manning Publications Co.
9. Brown, A., & Gopisetty, D. (2022, April 30). *Understanding Average Glucose, Standard Deviation, CV, and Blood Sugar Variability*. Retrieved from diaTribe.org: https://diatribe.org/diabetes-management/understanding-average-glucose-standard-deviation-cv-and-blood-sugar-variability
10. Brunner, S., Winter, R., Werzer, C., Stülpnagel, L., Clasen, I., Hameder, A., Sinner, M. F. (2021, 06 24). Impact of acute ethanol intake on cardiac autonomic regulation. *Scientific Reports*, p. 7. Retrieved from https://doi.org/10.1038/s41598-021-92767-y
11. Carrier, B., Helm, M., Cruz, K., Barrios, B., & Navalta, J. (2023). Validation of Aerobic Capacity (VO2max) and Lactate Threshold in Wearable Technology for Athletic Populations. Technologies. doi:10.3390/technologies11030071
12. Case, C., Mandrola, J., & Lennard, Z. (2017). The haywire heart. Boulder, Colorado: VeloPress.
13. Caserman, P., Yum, S., Göbel, S., Reif, A., & Matura, S. (2024). Assessing the Accuracy of Smartwatch-Based Estimation of Maximum Oxygen Uptake Using the Apple Watch Series 7: Validation Study. JMIR Biomedical Engineering. doi:10.2196/59459
14. Chalmers, T., Hickey, B., Newton, P., Lin, C.-T., Sibbritt, D., McLachlan, C., . . . Lal, S. (2022, 5 9). Associations between Sleep Quality and Heart Rate Variability:Implications for a biological model of stress detection using wearable technology. Interntional Journal *of Environmental Research and Public Health*, p. 10. doi:10.3390/ijerph19095770
15. Chidambaram, S., Maheswaran, Y., Patel, K., Sounderajah, V., Hashimoto, D., Seastedt, K., . . . Darzi, A. (2022). Using artificial intelligence:Enhanced sensing and wearable technology in sports medicine and performance optimisation. Sensors. Retrieved from https://doi.org/10.3390/s22186920
16. Freckmann, G., Schauer, S., & Beltzer, A. e. (2024). Continuous Glucose Profiles in Healthy People With Fixed Meal Times and Under Everyday Life Conditions. Journal of Diabetes Science and Technology, pp. 407-413. doi:10.1177/19322968221113341
17. Haleem, M. S., Cisuelo, O., Andellini, M., Castaldo, R., Angelini, M., Ritrovato, M., . . . Pecchia, L. (2024, 06). A self-attention Deep Neural Network Regressor for real time blood glucose estimation in paediatric population using physiological signals. Biomedical Signal Processing and Control, p. 9. doi:10.1016/j.bspc.2024.106065
18. Inchauspe, J. (2022). Glucose revolution. New York: Simon & Schuster.
19. Jarczok, M. N., Weimer, K., Braun, C., Williams, D. P., Thayer, J. F., Gündel, H. O., & Balint, E. M. (2022, 12). Heart rate variability in the prediction of mortality: A systematic review and meta-analysis of healthy and patient populations. Neuroscience & Biobehavioral Reviews. Retrieved from https://doi.org/10.1016/j.neubiorev.2022.104907
20. Kajisa, T., Kuroi, T., Hara, H., & Sakai, T. (2023). Correlation analysis of heart rate variations and glucose fluctuations during sleep. Sleep Medicine.
21. Mabe-Castro, D., Castillo-Aguilar, M., Mabe-Castro, M., Muñoz, R., Basualto-Alarcón, C., & Núñez-Espinosa, C. (2024). Associations between physical fitness, body composition, and heart rate variability during exercise in older people: exploring mediating factors. PeerJ. Retrieved from https://doi.org/10.7717/peerj.18061.

 doi:10.20944/preprints202602.0332.v1

22. Marasingha-Arachchige, S., Rubio-Arias, J. A., Alcaraz, P. E., & Chung, L. (2022, 11 24). Factors that affect heart rate variability following acute resistance exercise: A systematic review and meta-analysis. Journal of Sport and Health Science, p. 17
23. Strüven, A., Holzapfel, C., Stremmel, C., & Brunner, S. (2021, 04 19). Obesity, nutrition and heart rate variability. International Journal of Molecular Science, p. 14. doi:10.3390
24. Syem, I., Naimul, K., & Sri, K. (2021). Trends in Heart-Rate Variability Signal Analysis. Frontiers in Digital Health. doi:10.3389/fdgth.2021.639444
25. Zahedani, A. D., McLaughlin, T., Veluvali, A., Aghaeepour, N., Hosseinian, A., Agarwal, S., . . . Snyder, M. (2023, 11 25). Digital health application integrating wearable data and behavioral patterns improves metabolic health. npj Digital Medicine. doi:10.1038/s41746-024-00996-y
26. Sinning, C., Makarova, N., Völzke, H., Schnabel, R., Ojeda, F., Dörr, M., Felix, S., Koenig, W., Peters, A., Rathmann, W., Schöttker, B., Brenner, H., Veronesi, G., Cesana, G., Brambilla, P., Palosaari, T., Kuulasmaa, K., Njølstad, I., Mathiesen, E., Wilsgaard, T., Blankenberg, S., Söderberg, S., Ferrario, M., & Thorand, B. (2021). Association of glycated hemoglobin A1c levels with cardiovascular outcomes in the general population: results from the BiomarCaRE (Biomarker for Cardiovascular Risk Assessment in Europe) consortium. Cardiovascular Diabetology, 20. https://doi.org/10.1186/s12933-021-01413-4.