MACHINE LEARNING IMPLEMENTATION IN HEART RATE PREDICTION FOR RUNNING: A REVIEW

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ABSTRACT: One of the most important indicators of physiological health is the heart rate (HR), commonly used to understand exercise intensity, maximize training, and prevent overtraining or injury during endurance running. HR prediction accuracy is the key to building training strategies that are personalized wearable technology when influenced by noise or measurement errors. This paper review presents an analysis of the current ways of predicting heart rate during running, using modern machine learning or deep learning algorithms and the traditional statistical techniques. Conventional paradigms like linear regression are interpretable but usually restricted to nonlinear physiological responses. Machine learning algorithms, such as support vector machines, decision trees, and ensemble models have shown higher accuracy through the combination of several sensor-based variables, such as pace, distance, and workload. In more modern times, deep learning structures, especially recurrent and convolutional neural networks, have demonstrated a good promise in the modelling of complex temporal relationships in HR data. With these developments, issues persist in the fields of variability of data, model generalization and interpretability. This review has identified the present success, the major shortcomings, and future opportunities in the development of individualized, adaptive and explainable HR prediction models to improve performance and health in running.

KEYWORDS: *Heart Rate Prediction; Running; Machine Learning; Deep Learning; Wearable Technology*

1.0 INTRODUCTION

Heart rate (HR) is an important and simple physiological measure in determining exercise intensity, especially in endurance training such as running. It is an indicator of physical work because it signifies work by the heart that distributes blood and oxygen to the whole body. During running, heart rate is an important parameter to shows immediate outcomes of the way the body adapts to exercise. Monitoring HR allows athletes and coaches to monitor performance instantly, establish personalized training zones, and identify initial indications of fatigue or overtraining that could risk both performance and health [1].

Although this is important, direct HR measurement in the course of running is not without of limitations. The most common wearable devices that are based on either chest-strap electrocardiography (ECG) or wrist-based photoplethysmography (PPG), are subject to errors like sensor motion, noise, and sensor movement [2]. Existing fitness wearables such as Garmin or Coros also automatically determine HR thresholds but with pre-installed or pre-build, closed algorithms that are not open or user unable [3]. This can result in zone suggestions that are not precise, especially for runners whose training needs are varied. To overcome this, researchers have been applying Machine Learning (ML) more and more to tailor training programs. For instance, research suggested an ML-optimized recommendation system for marathon runners and other research applied ML to predict fatigue based on heart rate and Inertial Measurement Unit (IMU) data [4], [5]. These works demonstrate ML is effective for prediction and classification. In events with long distances, discomfort, limitation on battery life, and sensor cumulative drift can also make continuous direct measurement impractical. These problems lower the accuracy of uncontrolled raw HR data, especially in outdoors activities.

Proper forecasting of the heart rate has become a significant complement of the direct measurement. Predictive models can be used to predict the future behavior of heart rate during a run by adding factors of context, including pace and cadence, recovery time, lifestyle, age, weight, fitness status, and exercise response. This will enable athletes to proactively change before physiological stress becomes a critical concern [1], [6] . In addition to short-term monitoring, the personalized prediction facilitates the construction of adaptive training programs, which are based on the individual physiological profile of each runner, and thus, the safer and more effective performance increase.

The aim of this review is to provide a comprehensive overview of current techniques for heart rate prediction in running. It examines the computational approaches such as machine learning, while highlighting the strengths and limitations of each. This review also discusses the traditional formulas and the wearable technologies which are related to running. Special consideration is considered the gaps that are the most prominent, namely the absence of personalization of runners, the use of closed-source wearable algorithms, the lack of large, diverse data sets, and the difficulty of cross-device and cross-person generalization of models. Based on these findings, the review gives future directions of research, which includes addition of the multimodal sensors data, modelling (adaptive and personalized) and use Machine Learning to develop more precise and data-oriented systems to assist in safer and effective training.

The paper is organized into 6 main sections. The first section is the Introduction section, which contains the brief explanation and aim of the review. Section 2 is the Methodological Approach which describes the methodology used for the literature search and selection process for this review. Section 3 explains the techniques used for heart rate prediction in running, while Section 4 provides its challenges and limitation. Section 5 provides future directions in heart rate prediction for running and finally Section 6 concludes the review.

2.0 THE METHODOLOGICAL APPROACH

This paper conducts a Narrative Literature Review, intended to bring the results of articles concerning the topic of heart rate prediction in running with the help of wearable technologies. The review is aimed at classifying the implemented methodologies (Traditional/Statistical, Machine Learning, Deep Learning, and Hybrid Models) to vividly describe the technological advancement, which input data is essential, and general strengths, weaknesses, and typical performance measures (MAE/RMSE) of each category.

The review process focused on selecting relevant journals and conference publications related to heart rate prediction for endurance runners. Papers were collected from major scientific databases, including IEEE Xplore, ScienceDirect–Elsevier, Springer Online Journals, Frontiers, and MDPI, covering the period from 2018 to 2025. Relevant keywords such as 'heart rate prediction', 'running', 'wearable sensors', 'machine learning', 'deep learning', 'transfer learning', and 'hybrid physiological models' were used to identify potential studies. There were 112 publication papers from the year 2018 to 2025 that had been collected. After filtering based on closest relevance, 27 key articles were selected for the detailed reviews. In filtering, the redundant and unrelated articles were eliminated. The final selection includes 18 journal articles, 6 conference proceeding, 1 thesis (M.S.), and 2 online sources, covering studies on traditional regression approaches, machine learning methods, deep learning models, and hybrid or personalized prediction systems.

Figure 1 shows the flow of the review process which begins with the Planning, Conducting and finally the Reporting phases. This Narrative Literature Review has been adapted from [28]. In the Planning phase, the topic is selected, and the objectives are defined before validating the review. During Conducting phase, the literature review starts with the searching process, paper collection, paper elimination and finally analyzing the selected papers. The final phase is the Reporting which consists of synthesizing, concluding and finally the review reporting.

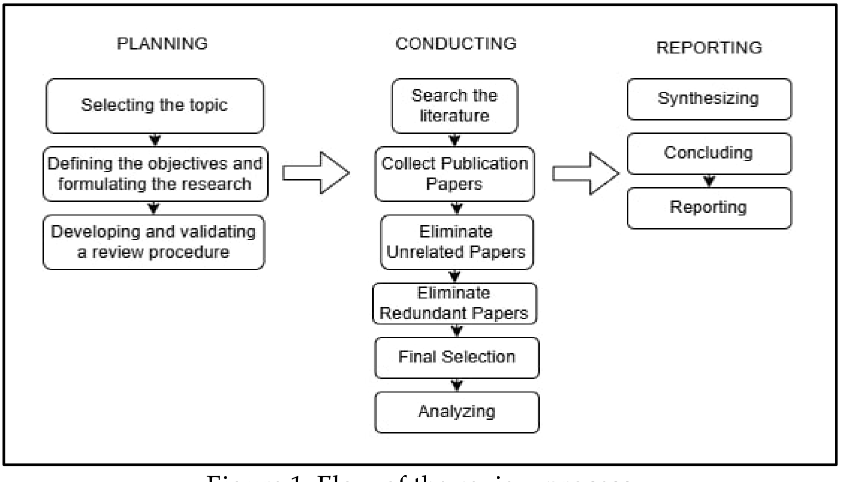

Figure 1: Flow of the review process

3.0 TECHNIQUES FOR HEART RATE PREDICTION IN RUNNING

Different techniques have been used to predict Heart Rate (HR) in running, ranging from simple formulas to advanced artificial intelligence. Table 1 presents the summary for the techniques that have been implemented for the heart rate prediction in running. Based on Table 1, the techniques used for heart rate prediction are categorized into Traditional or Statistical Models, Machine Learning Models, Deep Learning Models and Hybrid Models.

The Traditional or Statistical Models implement algorithms such as ARIMA and simple Linear Regression on variables such as HR time series and age [12, 14-19]. Though simple, and easy to interpret, they do not well with non-linear, dynamics of exercise, and therefore have a narrow range of accuracy. Beyond the statistical methods, there are Machine Learning (ML) Models, which include Random Forest (RF) and Support Vector Machine (SVM) [5, 7, 20-23]. These models employ refined wearable sensor capabilities for examples pace, cadence, Inertial Measurement Unit (IMU) data to deal with non-linear relationships and can be used in classification problems such as fatigue detection. They are not highly accurate (MAE: 3.0-6.5 BPM) and they need a large amount of manual feature extraction process to obtain meaningful data points.

The most recent technique is Deep Learning (DL) Models, which mostly implement Recurrent Neural Networks (RNN) and Long Short Term Memory (LSTM) models to process raw, sequential sensor signals [1, 3, 8, 10,11, 24-27]. DL models are also capable of automatic feature extraction and have the best performance at identifying deep temporal patterns, and hence the best accuracy of the non-hybrid methods (MAE: 2.0–4.5 BPM). They are however computationally intensive, data hungry and can be considered to be black-box systems because of low interpretability. Lastly, Hybrid Models are the most performance-oriented, as they incorporate ML/DL elements with noise-working methods (such as the Hybrid Conditional Framework) or they use them to be part of the Intelligent Recommendation Systems [2, 4, 6, 9, 13]. These models have the most robust and personalized results, with the highest accuracy (MAE: 1.5 -4.5 BPM). However, the complex architecture of these models may not suitable to be applied to certain simple design or real-time system implementation.

Table 1: Summary of techniques for heart rate prediction in running

Category	Algorithm / Model	Data Inputs	Strengths	Weaknesses	Perf. Metric	Ref.	Paper Library
Traditional / Statistical Models	ARIMA (Real-Time HR Forecasting)	Univariate HR time series data (historical HR), Age, Basic.	Simple; provides clear physiological insight.	Low Accuracy for dynamic prediction;	RMSE: 1.46 BPM	[7]	MDPI
	Functional Data Analysis	HR data from running sessions	Good for trend estimation and max HR prediction	Less robust to noise in outdoor running	RMSE: 7.035 BPM	[8]	IEEE Xplore Digital Library
	Age-based equations	Age, basic demographics	Easy to apply; provides baseline training zones	Large inter-individual error	Mean Diff.: -1.6 bpm	[9]	Frontiers (Official Journal Site)
	Velocity–HR regression	HR + velocity	Simple regression-based prediction	Sensitive to individual differences	RMSE: 4.05%	[10]	Science Direct (Elsevier B.V.)
	Linear Mixed Effects Model	Trunk Acceleration (IMU), HR data.	Mixed effects models handle both fixed effects	Limited predictive power	RMSE: 4.0 BPM	[11]	PLoS ONE (Public Library of Science)
	Linear Regression	Distance, Pacing Data, Historical Marathon Times.	Offers quick, simple estimates for race time.	Overly simplistic for complex systems like HR	N/A	[12]	Springer Link (Springer Nature)
	Linear Regression	Speed, Activity Type, Historical HR.	Provides a clear baseline for initial prediction steps.	Cannot capture complex non-linear physical	Accuracy 97.5%	[13]	Scopus
Machine Learning Models	SVM / Random Forest	Inertial Measurement Unit (IMU) data, Kinematics.	Effective for classifying intensity zones.	Less precise for regression	Accuracy: 85% - 95%	[14]	MDPI
	Gradient Boosting, Recommender ML	Mixed wearable data, user context	Handles nonlinear, useful for recreational runners	Requires careful tuning	MAE: 4.0 - 6.0 BPM	[15]	Science Direct (Elsevier B.V.
	Fatigue Classification ML	IMU + HR signals	Effective for detecting fatigue	Requires high-quality IMU placement	Accuracy 93.3%	[16]	MDPI
	PPG + ML	PPG sensor signals	Effective for wearable HR estimation, noise handling	Data quality critical	RMSE: 1.81 BPM	[17]	IEEE Xplore Digital Library

	Group vs Individual ML	GPS, pace, HR, training data	Insights into personalization for elite athletes	Group models less accurate	RMSE: 1.11	[18]	IEEE Xplore Digital Library
	Random Forest Regressor	Wrist Sensor Data (PPG, Accelerometer, Gyroscope).	Can clearly rank sensor features critical for prediction.	Accuracy struggles when motion dominates wrist-based signals.	Accuracy: 88%	[5]	University of Twente's institutional repository
Deep Learning Models	Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN)	Time-series HR, sensor signals	Captures temporal patterns, high accuracy	Requires large datasets, "black-box" issue	RMSE: 1.86 BPM	[19]	IEEE Xplore Digital Library
	CNN / LSTM on noisy PPG	PPG signals	Strong at denoising and temporal pattern learning	Needs training data and compute	MAE: 0.47 BPM	[20]	MDPI
	Assisted Living/HAR Systems	Sensor fusion (HR + activity)	Captures complex patterns, adaptive	Complex to deploy	N/A	[3]	MDPI
	Neural Nets with predefined route/ intensity	Route info + HR signals	Good for structured training prediction	Less generalizable	MSE: 0.0015	[21]	IEEE Xplore Digital Library
	Transfer Learning for threshold estimation	HR + pace + external conditions	Better generalization across individuals	Needs pre-trained models	MAE: 4.37 BPM	[22]	Science Direct (Elsevier)
	LSTM RNN NET	Course Profile (Elevation), Pacing strategy (Target Split Times), Speed.	Sequence-to-Sequence Prediction of future HR values based on a planned strategy.	Performance highly depends on the fidelity of the planned inputs	Accuracy: 61%	[23]	IEEE Xplore Digital Library
	Review/ Survey of AI/ Wearables	Surveys literature on AI in Sports Cardiology.	Provides a valuable synthesis of the role of AI/wearables in cardiovascular health.	Not a direct HR prediction model; a survey of the modeling approach.	N/A	[24]	ACS Publication
	Personalized Modeling (DL/RNN)	Wearables data (HR, Kinematics), Environment factors, Subject Metadata.	Highly Personalized; excellent at modeling complex	Requires extensive, high-quality personalized data over long time periods for training.	MAE: 6.1 BPM	[1]	Nature Portfolio
	LSTM Model	Accelerometer signals (X, Y, Z axes).	Automatic Feature Extraction directly from raw acceleration data.	Limited by the input: acceleration is an indirect measure of HR.	MAE: 3.0 - 5.0 BPM	[25]	Springer Link (Springer Nature)

Hybrid Models	Physiological + ML	Mixed wearable + physiological data	More personalized, better generalization	Complex, hard for real-time use	MAE: 5.2 BPM	[6]	MDPI
	Hybrid ML (ECG + ML)	ECG + clinical features	High accuracy, multi-feature	More suited for clinical than real-time running	Accuracy: 90% - 98%	[26]	IEEE Xplore Digital Library
	Edge ML (Hybrid Pipeline)	Novel Pressure Sensor Data, Accelerometer Data	Edge Computing Efficiency; Optimized for low-power, real-time use on wearable devices.	Performance is constrained by the limited processing power available on the edge device.	MAE: 2.39 BPM	[27]	IEEE Xplore Digital Library
	Intelligent Recommendation/ Optimization	Historical HR, Training Load, User Feedback (Goals).	Actionable Insights; Focuses on using model output to drive personalized.	The success depends on the prediction accuracy and the effectiveness.	Prediction MAE: 2-5 BPM	[4]	National Institute for R&D in Informatics (ICI)
	Hybrid Conditional Framework (MAICR)	Multiple Sensor Signals (PPG, ECG), Signal Quality Indicators (SQI).	Highly Robust; Combines ML for noise cleaning with DL for HR estimation	Complex Architecture; Challenging to design, train, and coordinate multiple distinct modules.	MAE: 1.5 - 3.5 BPM	[2]	Science Direct (Elsevier B.V.)

The bar chart in Figure 2 visualizes the number of papers across the four categories of techniques, as presented in Table 1. Based on Figure 2, the distribution reveals Deep Learning Models have the highest number, with 9 papers, followed by the Traditional/Statistical Models as the next most applied models with 7 papers. However, the Traditional/Statistical Models mostly have been implemented in the past research. The number of papers for Machine Learning Models is 6 papers, while the Hybrid Models has 5 papers. The rise of Deep Learning proves the shift of the field toward complex methods in favour of approaches that can process complex time-series data. It eventually aims at achieving a high level of performance in the personalized heart rate prediction.

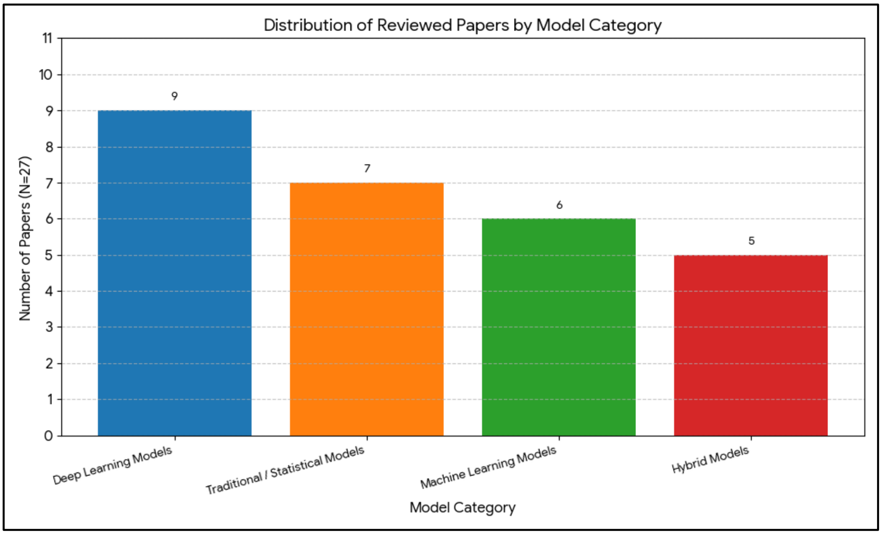

Figure 2: Number of Reviewed Papers by Model Category

3.1 Best Performance Technique

According to the performance indicators presented in Table 1, the present state-of-the-art solution to the problem of heart rate prediction is the Hybrid Models, with Multi-channel Adaptive Hybrid Conditional Framework (MAICR) [2]. This model has the lowest range of Mean Absolute Error (MAE) of 1.5 to 3.5 BPM, which is the most accurate and strong one [6, 11]. The model has been chosen as the best technique because it addresses the greatest weakness of all systems of wearable-based prediction motion noise [17, 27]. The MAICR is based on a strategy-sequenced architecture to attain its high performance:

i. ML-Based Noise Mitigation: The model uses a machine learning to examine Signal Quality Indicators (SQI) of raw sensor data (PPG or ECG). This component is also a dynamic filter to control noise due to movement of the runners, in order to produce high-quality data [14, 16].

ii. DL-Based Temporal Prediction: A Deep Learning (DL) element (LSTM) is then fed with the cleansed data. With good input, the DL model can invest all its resources in modelling complicated and lengthy time based connections in the heart rate series, so that it can optimize prediction precision [1, 26].

4.0 CHALLENGES AND LIMITATIONS

There are a few challenges that heart rate (HR) prediction during running encounters which influence the accuracy and usability of the research and its implementation. Despite the advancements witnessed in machine learning and wearable sensors in enhancing the prediction techniques, running in the real world is full of uncontrollable elements. The imprecision of modelling can be caused by individual differences, environmental conditions, and technical problems. These are some of the challenges that need to be overcome in order to enhance reliability and run real-time applications.

i. Limited availability of open datasets
   - Limitation of availability

   The other major limitation is the difficult access of large, open datasets of running HR data. Most of the published research is based on small or proprietary datasets and may be gathered in laboratory or semi-controlled environments. To give an example, Kayange et al. train on the FitRec dataset (around 38k runs, 665 users) but admit that it is not always representative of diverse real-world users (FitRec is skewed towards young male runners)[6]. Conversely, there are only a small number of very large studies, the Apple Watch dataset of 270,707 reported by research being referred to as one of the largest such studies to date in non-laboratory settings [1]. This means that a majority of the previous models have been exposed to significantly lower amounts of data. The lack of standardized, public benchmarks hinders fair comparisons and slows progress.

ii. Real-Time Wearable Deployment
   - Real-Time HR Prediction on Wearable

   HR predictors (deep neural networks, hybrid models, etc.) are most likely to be very heavy in computations or memory. Reliable constant operation of such models in a smartwatch or a fitness tracker may deplete battery and push hardware to its boundaries. According to recent research, most of the deep models are prohibitively large and power hungry to be implemented on embedded systems [27]. Even small weight DL pipelines can be hard on low-power hardware. Consequently, the trade-offs between the simplification of the models and the use of specialized TinyML techniques are important to reach real-time HR prediction on wearables, without losing excessive accuracy.

5.0 FUTURE DIRECTIONS

In recent years, there have been significant improvements in predicting heart rate (HR) during running, although further development is possible. New technologies, bigger datasets, and more sophisticated models are creating an opportunity to get predictions more accurate, individualized, and helpful in actual running scenarios. Future directions are developing models that can more easily accommodate each runner, execute in other populations, provide clear explanations, operate on wearable devices in real time, and combine multiple data sources. These guidelines can be used to enhance training, performance, and health among runners.

A major future direction is building personalized heart rate (HR) models that adapt to each runner's unique physiology and training history. Indicatively, Nazaret et al. created a hybrid model with over 270,000 workout sessions having a median error of approximately 6.1 beats per minute (BPM) and explaining approximately 81% of the variation in maximal oxygen uptake (VO 2 max) [1]. Their model also estimated the ability of the environment heat to increase HR by approximately 10% [1]. In the same vein, Kayange et al. suggested a model that uses a combination of Dynamic Bayesian Network and Long Short-Term Memory (LSTM) networks to learn through recent training data. Their system was able to reach approximately 5.2 BPM error and give real time recommendations as the exercise continued [6]. Online learning or federated learning is anticipated to be utilized in the future to ensure that the model continues to adapt as fitness, fatigue, or health of a runner evolves with time.

Another promising direction is using transfer learning to adapt models to different types of runners. A model that is trained on a large set of young athletes, for example it can be fine-tuned on smaller sets to perform with older or less experienced runners. It has been demonstrated that this approach enhances performance of machine learning when the amount of data is small [22]. Transfer learning can be applied to make HR prediction models more inclusive, including groups that are underrepresented like female runners, novice runners, or elite athletes without individually large new datasets.

To ensure that heart rate prediction is useful in training, models must not only produce accurate predictions, but they must also produce the explanations of why the predictions are produced. Physiological models are easily interpretable since they can actually show how different factors like heat or humidity affect the HR responses [1]. Recent explainable artificial intelligence (XAI) systems or attention mechanisms, have the ability to indicate which of the inputs, including pace, terrain, or gait, has the most significant impact on a prediction [24]. Such descriptions in running apps would help coaches and athletes to make sense of the reasons behind HR spikes, which would improve trust and make prediction more feasible training and even in racing.

Another important field of development is real-time prediction on wearable devices. Such models must be fast, energy-efficient and capable of constantly updating as new sensor data arrives; simple models can even be surprisingly effective, as De Sabbata and Simonini discovered that simple time-series models (ARIMA) were not much worse than deep neural networks at short-term prediction [7]. More complex models (such as the DBN+LSTM model by Kayange et al.) already demonstrate that they can provide real-time guidance forecasting the HR trends and providing pacing recommendations during running [6]. The goal of future work is to fit these models into smartwatches so that they can process them directly on the device, providing immediate feedback and customizing the settings according to the user without going through cloud computing.

Lastly, using more than one source of data will allow future HR prediction models to be better. Wearable devices have also become able to gather Global Positioning System (GPS) data (pace, distance, elevation), inertial sensor data (cadence, stride), and physiological data (photoplethysmography (PPG)) to measure HR and heart rate variability (HRV). The combination of these various inputs can enable more accurate and stronger predictions. As an example, GPS-derived variables and HR data were applied by Kayange et al. [6], whereas Nazaret et al. took into consideration such environmental factors as temperature and humidity, demonstrating their strong effect on HR [1]. The models can be more accurate by adding measures of factors that cause changes in HR, like speed vs. fatigue, such as HRV or metabolic indicators (like estimated VO_2 or lactate) in the real running environment.

6.0 CONCLUSION

This review has provided the analysis on the current techniques that have been implemented for the heart rate prediction in running. It also presents the challenges, limitations and the future direction of heart rate predictions in running sports. It could be seen that the development of heart rate (HR) prediction of running has progressed at an accelerated pace, starting with basic models based on regression to machine learning and currently onto deep learning. More complex and dynamic physiological patterns could be better represented using modern ML and deep learning methods than traditional models, which were easier to interpret but usually not as accurate. The advancements in Machine Learning based techniques could offer advantages such as stamina and injury avoidance. Proper HR prediction assists the runners to train with the right intensity, fatigue, and overexertion. It also assists coaches in organizing more effective and safer training programs. Future research must aim to create personalized predictive models of HR, understandable and capable of real-time operation so that they become more approachable to use in day-to-day training with wearable devices. In general, future directions also should focus on explainable AI, transfer learning that can use wider generalization, integration with digital twins and smart coaching platforms, and real-time adaptive training suggestions to improve the performance and usability of AI in real-world running situations. The significance of this review is that it can contribute to SDG Goal 3 of Good Health and Well-Being, by providing knowledge and insights in facilitating more efficient and safer running exercise through data driven and machine learning or AI solutions.

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