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PERSONAL HEALTH INDEX (PHI): AN AI-BASED APPROACH TO ATHLETE WELLNESS MONITORING

Shyam Paryani, Mei Zhao, Rob Haley, Evan Kilby, Kendall Chassman*

University of North Florida, Jacksonville, Florida, USA

Correspondence: s.paryani@unf.edu

ABSTRACT

The integration of wearable technology and artificial intelligence (AI) has opened new possibilities for personalized health monitoring. This article introduces the Personal Health Index (PHI), a proprietary metric developed to assess individual wellness using data collected from wearable devices. Implemented our institution. The PHI system has been in use since 2022 to monitor athletes across multiple sports. By leveraging AI to analyze physiological data, PHI provides actionable insights that support training, recovery, and overall health optimization.

KEYWORDS

Personal Health Index, Artificial Intelligence, Wearable Devices, Athlete Monitoring, Remote Patient Monitoring, VO_2 Max, Sleep Efficiency

INTRODUCTION

Wearable devices such as Fitbit and Apple Watch have become ubiquitous tools for tracking health metrics. Despite their popularity, the challenge remains in converting raw data into meaningful health assessments. The Personal Health Index (PHI) was developed to address this need by offering a comprehensive, AI-driven score that reflects an individual's overall wellness. This system is particularly valuable in athletic settings, where continuous monitoring and rapid feedback are essential for performance and injury reduction.

Wearable technology can track physical activity, sleep patterns, and heart rate, offering valuable data for health monitoring, although reliability may vary across different metrics and devices [1,2]. Piwek et al. [1] highlighted both the promises and limitations of consumer health wearables, emphasizing the need for better integration with clinical systems. Patel et al. [2] argued that wearables should be viewed as facilitators of behavior change rather than standalone solutions. Bunn et al. [3] reviewed the reliability of commercial wearable devices and found that while most devices were accurate in step counting, but variability existed in heart rate and sleep tracking.

In the context of athletic performance, wearable devices have been used to monitor training load, recovery, and cardiorespiratory fitness. Wang et al. [4] discussed the potential of wearable sensors for real-time health monitoring, while Kooiman et al. [5] evaluated the validity of ten consumer-grade activity trackers. Baig et al. [6] conducted a systematic review of wearable patient monitoring systems and identified key challenges in clinical adoption, including data privacy and interoperability. The integration of AI into wearable health monitoring has further enhanced the ability to analyze large datasets and generate personalized insights [7].

Guidelines from the World Health Organization [8] and national health agencies [9] support the use of technology to promote physical activity and reduce sedentary behavior. Thompson [10] reported that wearable technology continues to be among the top global fitness trends, indicating widespread acceptance and potential for impact. A recent report on cheerleading illustrated the use of AI in athletic monitoring reflecting a broader trend of leveraging advanced technologies to optimize athletic performance and monitoring across diverse disciplines [11].

METHODS

The PHI system can collect data from a range of devices including smartwatches, pulse oximeters, weight scales, heart rate monitors, and blood pressure cuffs. Metrics monitored include sleep efficiency, body mass index (BMI), VO_2 max, step count, and active minutes. A custom mobile application synchronizes with wearable devices, automatically retrieving and analyzing daily wellness data. The AI algorithm processes this data to generate a daily PHI score, which is used to guide training and health decisions.

The development and implementation of the PHI followed a structured methodology, combining wearable technology integration, data analytics, and field testing. Initially, a set of physiological metrics was identified based on relevance to athletic performance and general wellness. These metrics included sleep efficiency, BMI, VO_2 max, step count, and active minutes. Data was collected using commercially available such as Fitbit and Apple Watch, supplemented by pulse oximeters, weight scales, heart rate monitors, and blood pressure cuffs.

A custom mobile application was developed to synchronize data from these devices and transmit it to a secure server. The AI algorithm was trained using historical data to generate a personalized PHI score. The system was piloted with athletes from the University of North Florida (UNF), and feedback was collected to refine the algorithm and user interface. This study was approved by the UNF Institutional Review Board (protocol code IRB#1970666-2, date: 18 January 2023), and all participants provided written informed consent before participating in this study.

Statistical analysis, including Mann-Whitney U tests and Spearman's rank correlation, was used to investigate the relationships between PHI scores and performance metrics.

AI MODEL TRAINING AND VALIDATION

The accuracy and reliability of the PHI score depend on the robustness of the underlying AI model. The model is trained using a large dataset of physiological metrics collected from wearable devices. Data preprocessing includes normalization, outlier detection, and feature selection to ensure high-quality inputs. The model employs supervised learning techniques, with labeled data indicating wellness levels based on expert assessments and historical performance. Validation of the AI model involves cross-validation and testing on independent datasets to assess generalizability. Performance metrics such as precision, recall, and F1-score are used to evaluate the model's effectiveness. Continuous monitoring and retraining are conducted to adapt to new data and improve accuracy over time. Transparency in model development and validation is critical to building trust among users and stakeholders.

RESULTS

Since its launch in 2022, the PHI system has been adopted by several athletic teams at UNF. Basketball, Soccer, Track & Field, Tennis, Volleyball, Softball, and Cheerleading teams have been monitored. With 17,631 records, using Spearman's rank-order correlation, five variables were analyzed. The number of daily steps, sleep efficiency, and active minutes were positively correlated with an athlete's PHI. BMI and VO2Max were not strongly correlated to the daily PHI.

FIGURE 1: CORRELATION OF METRICS COLLECTED ON ATHLETES WITH PHI USING SPEARMAN'S RANK-ORDER CORRELATION.

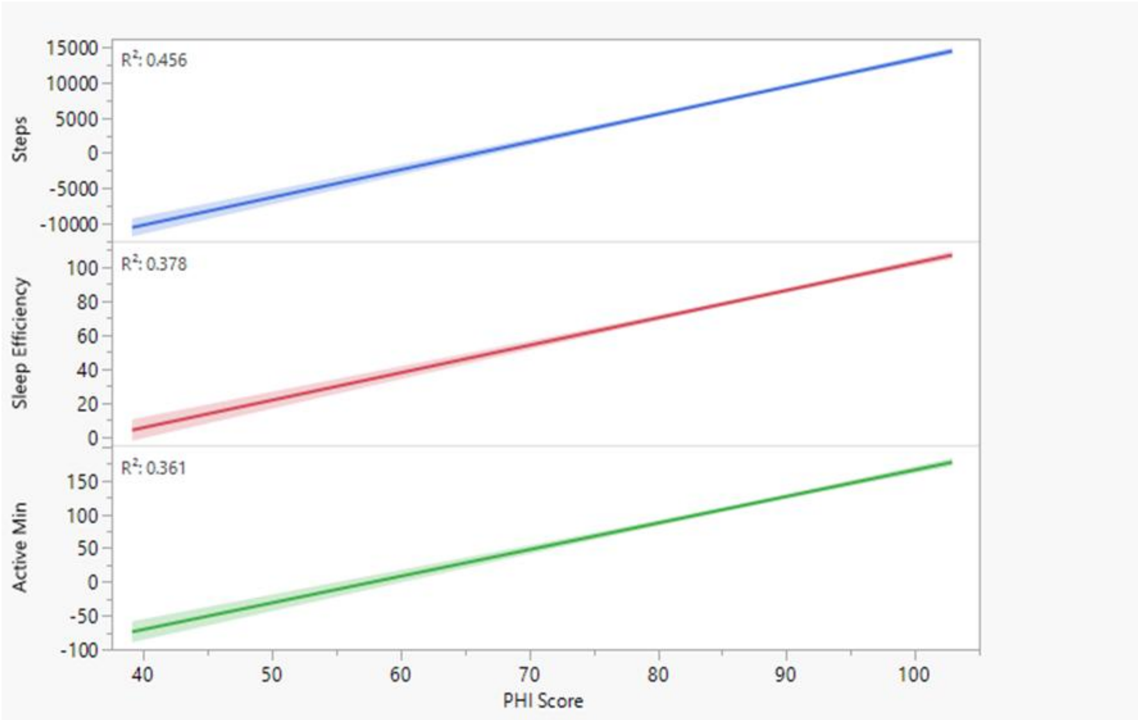

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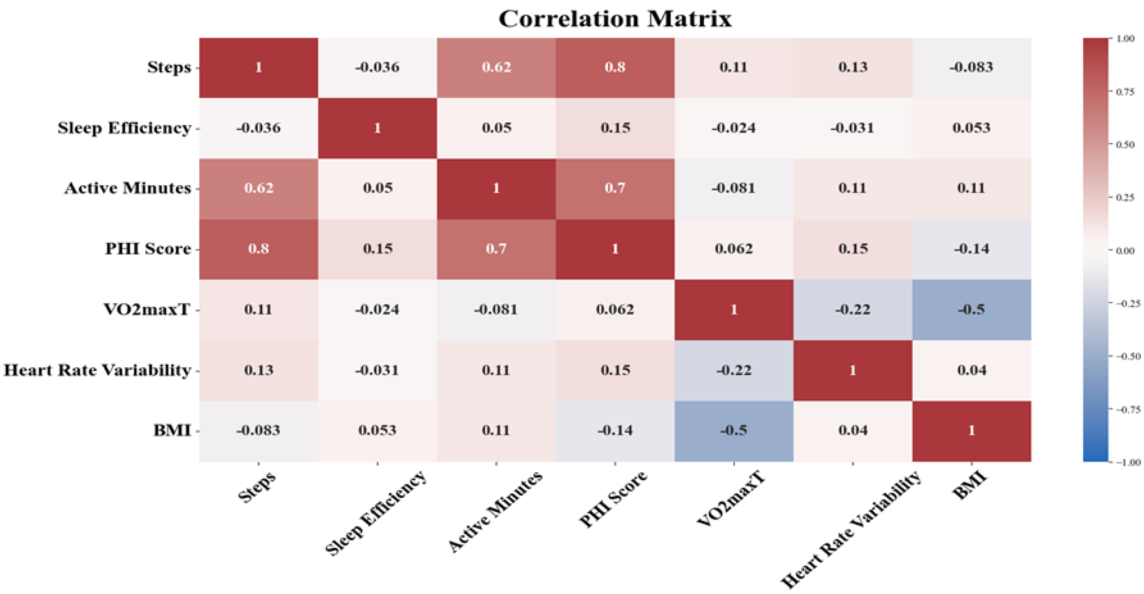
Figure 2 illustrates the correlation between the PHI score and its constituent metrics across data collected for all sports. Daily number of steps, sleep efficiency, and active minutes were strongly correlated with the daily PHI score.

FIGURE 2: CORRELATION MATRIX FOR ALL SPORTS USING SPEARMAN'S RANK CORRELATION COEFFICIENT



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DISCUSSION

The PHI system offers several advantages, including efficient health monitoring, early risk detection, and personalized recommendations. It provides a validated daily health score that can be used by athletes, coaches, and healthcare providers to make informed decisions. The system also enables multivariate analysis of health metrics, identifying strong correlations between activity levels, sleep quality, and overall wellness [2,3]. Beyond athletics, PHI has potential applications in fitness centers and general population health monitoring [4,5]. Its ability to integrate diverse data streams positions it as a valuable tool for preventive care and personalized health strategies. As wearable technology and AI continue to evolve, systems like PHI could play a pivotal role in bridging the gap between consumer health data and clinical decision-making.

The PHI system is poised for expansion beyond collegiate athletics. Future enhancements include integration of in-game statistics and GPS data to correlate physical performance with health metrics. Development of team and individual dashboards will allow coaches and athletes to visualize trends and make informed decisions. Additionally, the system may be adapted for use in fitness centers, corporate wellness programs, and general population health monitoring. Research partnerships and longitudinal studies will help validate the PHI score across diverse demographics. The goal is to establish PHI as a standard tool for personalized health assessment and proactive wellness management.

Future research on the Personal Health Index (PHI) should focus on several key areas to enhance its utility and impact. First, large-scale longitudinal studies are needed to evaluate the long-term effects of PHI-guided interventions on health outcomes across diverse populations. These studies should include both athletic and non-athletic cohorts to assess generalizability. Second, research should explore the integration of PHI with electronic health records (EHRs) to facilitate seamless data exchange between personal monitoring systems and clinical workflows. This would enable healthcare providers to incorporate PHI scores into routine care and decision-making. Third, further development of the AI algorithm is essential, including the use of advanced machine learning techniques such as deep learning and reinforcement learning to improve predictive accuracy and personalization. Additionally, studies should investigate user engagement strategies, including gamification and behavioral nudges, to promote sustained use of the PHI system. Finally, ethical and policy research is needed to address concerns related to data privacy, algorithmic bias, and equitable access to wearable health technologies. By addressing these areas, future research can ensure that PHI evolves into a robust, inclusive, and clinically valuable tool for health monitoring and management.

While these research priorities will shape PHI's evolution, translating them into practice requires a structured implementation strategy. Successful implementation of the PHI system requires a multi-faceted approach that includes stakeholder engagement, infrastructure readiness, and training. Institutions should begin by identifying key personnel such as athletic trainers, IT specialists, and healthcare providers who will oversee deployment. Infrastructure must support secure data transmission and storage, and wearable devices must be compatible with the PHI platform. Training programs should be developed to educate users on device usage, data interpretation, and response protocols. Pilot testing and phased rollouts can help identify challenges early and ensure smooth integration. To evaluate the effectiveness of PHI, comparative studies should be conducted against existing health monitoring tools. Metrics such as user satisfaction, health outcomes, and cost-effectiveness can be used to assess performance. For example, PHI can be compared with traditional fitness assessments or manual tracking methods. Preliminary findings suggest that PHI offers superior real-time feedback and personalized insights, which may lead to improved adherence and outcomes. Further research is needed to validate these advantages across different populations and settings.

To complement these research efforts, incorporating user feedback helps refine functionality and address real-world challenges. User feedback is essential for refining the PHI system and ensuring it meets the needs of diverse users. Surveys and interviews with athletes, coaches, and healthcare providers can provide insights into usability, accuracy, and impact. Common themes include appreciation for the simplicity of the PHI score, desire for more customization options, and concerns about data privacy. Feedback should be systematically analyzed and incorporated into iterative design updates. Engaging users in the development process fosters trust and improves adoption.

Incorporating user feedback not only improves usability but also informs the adaptations needed for successful scaling across diverse contexts. The scalability of PHI to global contexts depends on its adaptability to different healthcare systems, cultural norms, and technological infrastructures. Localization of the app interface, language support, and integration with regional health databases are critical for international deployment. Partnerships with global health organizations and academic institutions can facilitate cross-border research and implementation. By addressing barriers such as device affordability and internet access, PHI can become a valuable tool for global health monitoring and equity.

CONCLUSION

The Personal Health Index represents a significant advancement in digital health and sports science. By combining wearable technology with AI analytics, PHI transforms raw data into meaningful insights that support wellness and performance. Its successful implementation at UNF demonstrates its value in athletic settings and its potential for broader application in personal and community health initiatives [6,7].

Healthcare professionals and athletic trainers can leverage the PHI system to enhance patient and athlete monitoring. By integrating wearable technology into routine assessments, practitioners can obtain real-time insights into an individual's health status. The PHI score simplifies complex data into a single metric, facilitating quick decision-making.

Practitioners should encourage consistent device usage and educate users on interpreting their PHI scores. In cases of moderate or high risk, timely interventions such as consultations, diagnostic testing, or treatment plans can be initiated. Collaboration with exercise science departments can further enrich the monitoring process by incorporating academic research and performance analytics.

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