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Towards Smart Wearables as Digital Metabolic Twins: Algorithmic Estimation of Nutrient Depletion During Exercise

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Towards Smart Wearables as Digital Metabolic Twins: Algorithmic Estimation of Nutrient Depletion During Exercise

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Abstract

Wearable devices and health applications have transformed the monitoring of exercise performance, providing metrics such as heart rate, step count, distance travelled, calories burned, and recovery time. While current algorithms primarily estimate energy expenditure, long-standing evidence suggests that exercise induces systematic depletion of electrolytes, glycogen, vitamins, and other nutrients. Integrating physiological models with wearable sensor data could enable the estimation of these metabolic parameters, effectively creating a digital metabolic twin. This opinion explores the current advances in wearable monitoring, highlights the physiological basis for nutrient depletion, and discusses the feasibility of algorithmic approximation of broader metabolic changes. Incorporating these capabilities into wearable technology offers a new avenue for precision exercise physiology, with potential applications in personalized nutrition, training optimization, and disease prevention.

Keywords: wearable devices; digital metabolic twin; nutrient depletion; exercise physiology; glycogen and electrolytes

I. Introduction

Advances in wearable technology have enabled the continuous monitoring of physiological parameters, facilitating personalized exercise medicine and recovery assessment. Smart watches (Figure 1) and fitness applications routinely quantify steps, heart rate, distance, and estimated caloric expenditure using accelerometers and photoplethysmography (PPG) sensors [4,16].

Figure 1. Conceptual overview of a digital metabolic twin using wearable devices. The smart watch collects real-time physiological data, including heart rate, motion, and activity intensity. These data streams are processed through algorithmic models integrating physiological knowledge and user-specific parameters to estimate dynamic changes in energy expenditure, glycogen utilization, electrolyte, and vitamin status during exercise.

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The digital metabolic twin can provide personalized feedback for training optimization, recovery guidance, and nutritional adjustments. Image attribution: Assia Benkerroum, sourced from: https://www.flaticon.com/free-icon/smartwatch_8578929?term=smartwatch&page=1&position=81&origin=search&related_id=8578929, accessed on 05/10/2025).

Despite these capabilities, current devices largely focus on energy metrics, neglecting the broader metabolic consequences of exercise. Physical activity induces depletion not only of macronutrient stores but also of micronutrients, including electrolytes and vitamins, and alters glycogen availability across muscle and liver stores [2,3].

A growing body of literature indicates that nutrient depletion can influence performance, recovery, and long-term health [11,12]. Sodium, potassium, magnesium, and calcium are lost through sweat at rates dependent on exercise intensity, duration, environmental conditions, and individual physiology [20]. Similarly, water-soluble vitamins, such as B-complex and vitamin C, participate in energy metabolism and oxidative stress mitigation, becoming depleted during prolonged or high-intensity activity [14,15]. Glycogen stores, critical for sustaining exercise, are depleted in a rate-dependent manner that varies by fibre type, intensity, and prior nutritional status [5,6].

Even though the physiological basis is well established, no current wearable system attempts to estimate nutrient depletion through algorithms. The concept of a digital metabolic twin—wherein a personalized model integrates physiological data to estimate energy, macronutrient, and micronutrient dynamics—represents a novel avenue in exercise science.

Wearable Technology and Energy Monitoring

Modern wearables integrate accelerometers, gyroscopes, optical heart rate sensors, and sometimes electrocardiography (ECG) to provide real-time exercise metrics. Algorithms estimate energy expenditure using heart rate, activity intensity, and biomechanical movement [10]. Caloric calculations typically rely on generalized metabolic equivalents (METs) adjusted for individual anthropometrics [1]. However, these estimations do not account for nutrient-specific depletion, nor do they consider biochemical markers such as electrolyte loss, glycogen utilization, or vitamin turnover.

Electrolyte and Vitamin Monitoring via Algorithms

Exercise-induced electrolyte depletion can be inferred indirectly from sweat rate, heart rate variability, and environmental conditions [7,20]. Sodium and potassium losses correlate with sweat volume and exercise intensity [20], whereas magnesium and calcium depletion, although smaller, influence neuromuscular function [13]. Water-soluble vitamins such as B group and vitamin C are consumed in biochemical reactions supporting ATP production and oxidative stress mitigation; their depletion rates correlate with exercise intensity and duration [14,15]. Algorithmic estimation could integrate real-time sensor data, user-specific parameters, and physiological models to provide approximate micronutrient loss during activity.

Glycogen and Metabolic Spectrum Estimation

Glycogen depletion is central to exercise fatigue, with rates influenced by exercise type, intensity, and training status [6]. Wearable proxies, including heart rate response, oxygen consumption, and activity intensity, could feed predictive algorithms to estimate muscle and liver glycogen utilization [6]. Beyond glycogen and vitamins, integrated metabolic spectrum models could predict shifts in substrate utilization, fluid balance, and oxidative stress markers, enabling comprehensive monitoring of physiological strain [17,18]. Such models could incorporate individual differences, environmental factors, and dietary intake to generate a personalized metabolic profile during exercise.

Discussion

Integrating nutrient depletion algorithms into wearable devices requires multidisciplinary collaboration across physiology, bioinformatics, and sensor engineering. Validation studies would need to compare algorithmic predictions against biochemical measures of electrolytes, vitamins, and glycogen using blood, urine, or sweat assays [7,19]. Machine learning approaches could improve prediction accuracy by leveraging large datasets of exercise physiology metrics and individual metabolic responses [4,6]. Ultimately, wearable-enabled digital metabolic twins could support individualized training plans, dietary adjustments, and early detection of deficiencies or overtraining.

The current limitations of wearable devices are focused largely on energy expenditure, which indeed represent an opportunity for innovation. Algorithmic estimation of nutrient depletion could extend the utility of wearables beyond basic exercise monitoring to comprehensive metabolic management. Such integration would advance personalized exercise physiology, optimizing performance, recovery, and long-term health outcomes. While direct biochemical measurement remains the gold standard, computational models incorporating sensor data and physiological knowledge can provide meaningful approximations in real time. By combining wearable monitoring with predictive modelling, these digital metabolic representations could provide a practical approach to this challenge.

II. Conclusion

The convergence of wearable technology, physiological modelling, and algorithmic computation presents a unique opportunity to expand exercise monitoring beyond calories to encompass electrolytes, vitamins, glycogen, and broader metabolic states. Digital metabolic twins could transform personalized training, nutrition, and health optimization, representing an avenue in digital health. Further research integrating sensor data, physiological models, and machine learning is necessary to validate and refine these approaches.

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