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Correlation between sweat and blood biomarkers for physiological monitoring in humans: a scoping review

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Abstract. Continuous, real-time health monitoring has driven growing interest in non-invasive biochemical strategies, highlighting human sweat as a promising biofluid due to its rich biomarker composition. Despite advances in the development of sweat-based wearable sensors, the lack of clinically validated standards and inconsistencies in the correlations between sweat and blood analytes—considered the gold standard in clinical practice—still limit their widespread application. These discrepancies arise from physiological and methodological factors, including secretion mechanisms, sweat rates, induction and collection methods, and skin contamination. This review critically compiles and analyzes the available evidence on the relationship between sweat and blood biomarkers, identifying existing gaps, methodological limitations, and future perspectives, and emphasizing the need for approaches grounded in the physiology of sweat glands to advance non-invasive physiological monitoring.
Keywords: Health monitoring; Non-invasive monitoring; Physiological biomarkers; Sweat analysis; Sweat–blood correlation

Introduction

The demand for continuous and real-time health monitoring has increased considerably, driving the emergence of new biochemical analysis strategies, particularly non-invasive techniques. In this context, human sweat has emerged as a particularly promising biofluid. Its relevance for autonomous physiological monitoring stems from its complex composition, which includes a wide variety of biomarkers, such as proteins, lipids, metabolites, and other small molecules capable of providing valuable information about an individual's health status (Bandodkar, Ghaffari & Rogers, 2020).

In recent years, numerous studies have focused on developing viable prototypes of sweat-based wearable sensors. However, one of the main challenges identified is the lack of clinically validated standards for the analysis of this biofluid. Since blood remains the gold standard for biofluid analysis in modern medicine, establishing the relationship between analytes present in sweat and those found in blood is a fundamental requirement (Zheng, 2025).

From a physiological perspective, the anatomical proximity of sweat glands to the dermal capillary network facilitates the passive diffusion of blood-derived constituents into sweat, providing a potential pathway for determining correlations between analytes present in these two biofluids (Lu et al., 2025). Nevertheless, few studies involving sweat-based wearable sensors discuss the composition of this biofluid from a physiological standpoint, an aspect that is essential for understanding the mechanisms underlying the production and secretion of biomarkers of interest. Despite the theoretical promise and growing interest in sweat-based diagnostics, significant gaps remain in the understanding of these correlations. For most constituents, sweat–blood relationships have either not yet been established or have yielded conflicting results (Baker & Wolfe, 2020).

These inconsistencies may be attributed to multiple factors, including the method of sweat induction, collection strategies, variations in sweat rate, contamination from the skin surface, and differences in the mechanisms by which biomarkers

are produced or secreted by sweat glands. Such factors contribute to a complex relationship between sweat and blood that does not always reflect a direct and proportional correlation between analyte concentrations (Yang et al., 2025).

Contextualization and analysis

Establishing the relationship between analytes present in sweat and their corresponding blood levels is an essential prerequisite for the development of clinically validated standards and for highlighting the potential of sweat as a less invasive alternative to blood. Therefore, the present scoping review aims to compile and critically analyze the available evidence regarding the correlation between sweat and blood biomarkers, highlighting the main methodological limitations and reported inconsistencies, as well as discussing future perspectives for advancing this field.

Material and Methods

The methodological stages of this review were conducted in accordance with the framework proposed by the Joanna Briggs Institute (JBI) Manual for Scoping Reviews. This framework was originally developed by Arksey and O'Malley (2005) and subsequently refined by Levac et al. (2010) and Peters et al. (2015). The methodological process consists of the following stages:

i. Identification and alignment of the review objective(s) and research question(s);
ii. Development and alignment of the inclusion criteria with the review objective(s) and research question(s);
iii. Description of the planned approach for evidence searching, study selection, data extraction, and presentation of the evidence;
iv. Identification of the evidence through a systematic search process;
v. Selection, extraction, and analysis of the evidence;
vi. Presentation of the results;
vii. Synthesis of the evidence in relation to the review objective, presentation of conclusions, and discussion of the implications of the findings.

Research Question and Search Strategy

The guiding research question was developed based on the PCC framework (Population, Concept, and Context). The Population comprised human individuals, with no restrictions regarding sex or age group. Regarding the Concept, the review investigated the relationship between biomarkers present in sweat and blood within the Context of health monitoring. Accordingly, the research question was defined as: What evidence is available in the literature regarding the relationship between biomarkers measured in sweat and blood in human individuals in the context of physiological monitoring?

The literature search was conducted using the CAPES Journal Portal and the Scopus database, both of which provide access to a broad range of scientific publications, as well as PubMed, which is primarily focused on biomedical literature. The keywords and corresponding descriptors used to address the objective of this review were: (Blood OR Serum) AND Sweat AND Biomarkers AND Correlations.

Inclusion and Exclusion Criteria

Given the numerous inconsistencies identified in a previous study on this topic, only articles published from 2020 onward were included in this review. Studies that did not report correlations between sweat and blood biomarkers, or that contained only superficial references with limited relevance to the objectives of this review, were excluded.

Study Selection and Data Extraction

The Rayyan software was used during the screening, study selection, and data extraction stages. Initially, duplicate records were automatically identified and removed by the software. Subsequently, titles and abstracts were screened according to the predefined eligibility criteria. Full-text articles were then assessed to verify their compliance with the inclusion criteria. Finally, the selected studies were re-examined to identify information relevant to the development of this review.

The extracted data included the physiological aspects of the biomarkers and their associated conditions, the correlations identified between sweat and blood biomarkers, the physiological characteristics of sweat itself, factors influencing potential errors in the observed correlations, and future challenges related to the topic.

Results and discussion

The search identified a total of 125 articles, of which 3 were retrieved from the CAPES Journal Portal, 73 from Scopus, and 49 from PubMed. The sweat biomarkers identified in the studies included in this review that demonstrated some degree of correlation with their corresponding blood levels, as well as the factors influencing these correlations, are discussed below.

Physiological Perspective of Sweat

In the human body, sweat glands can be classified into three main types: eccrine, apocrine, and sebaceous glands. The anatomical proximity of these glands to the dermal capillary network facilitates the diffusion of blood-derived constituents into sweat, providing this biofluid with potential equivalence to blood for physiological monitoring applications (Lu et al., 2025).

Among the primary functions of sweat, thermoregulation stands out as a key process mediated by heat loss through the evaporation of

water secreted onto the skin surface. During physical exercise, activation of the sweat glands increases the sweat rate, thereby contributing to body cooling. This rate varies across different body regions, as approximately two to four million sweat glands are distributed heterogeneously throughout the skin surface (Dai, Lu, & Zhou, 2025).

In addition to thermoregulation, sweat glands play an important role in maintaining skin surface homeostasis due to the complex composition of sweat, which contains a wide variety of solutes, including proteins, lipids, metabolites, and other small molecules. This diversity of analytes may reflect specific physiological conditions, such as hydration status, among other clinically and physiologically relevant parameters (Spano et al., 2025).

A more comprehensive understanding of the sweating process requires consideration of molecular partitioning in sweat, which refers to the transport mechanism by which biomarkers move from the bloodstream into this biofluid. Although this topic has received limited attention in studies focused on the development of sweat-analysis technologies, an insufficient understanding of partitioning mechanisms may lead to the premature exclusion of promising biomarkers, particularly when an apparently weak correlation is observed between blood and sweat concentrations (Sonner et al., 2015).

Biomarker transfer is constrained by an epithelial barrier that separates blood from sweat, allowing transport through only two primary pathways: transcellular transport, which occurs through cells, and paracellular transport, which occurs between cells. Small molecules, such as cortisol and ethanol, are able to diffuse across the cellular lipid bilayer and reach sweat at concentrations similar to those found in blood. In contrast, larger molecules, such as glucose and proteins, rely predominantly on the paracellular pathway, resulting in substantial dilution. Consequently, many biomarkers with potential utility for physiological monitoring may be present in sweat at concentrations below the detection limits of certain biosensors (Jajack et al., 2018).

Correlations Between Sweat and Blood Reported in the Literature

I. Lactate

Lactate is one of the most extensively investigated exercise-related biomarkers in sweat. In addition to being a byproduct of anaerobic glycolytic metabolism, lactate plays important roles in cellular metabolism, energy homeostasis, and intercellular signaling processes, including the regulation of gene expression, immune responses, and adaptive physiological mechanisms (Yang & Yan, 2025). Its concentration in biological fluids is strongly associated with exercise intensity and the onset of muscle fatigue, which justifies its widespread use as a non-invasive marker of metabolic status in sports science (Dai, Lu, & Zhou, 2025). Monitoring lactate levels provides essential parameters for optimizing training programs, contributing to the prevention of overtraining and the reduction of injury risk in athletes (Yang & Yan, 2025).

Beyond athletic performance, elevated lactate concentrations may also be associated with severe clinical conditions, such as sepsis, respiratory or cardiac failure, and hepatic dysfunction (Yang & Yan, 2025). In this context, Yang et al. (2025), in their review, highlighted a study conducted by Xuan et al. (2023) as an example of a device that reportedly demonstrated a strong correlation between sweat and blood lactate levels. However, although the study showed satisfactory performance in quantifying sweat lactate using a Prussian Blue-based biosensor, direct correlations between sweat and blood concentrations were not actually reported. Instead, the authors presented only a Pearson correlation coefficient of 0.97 between the developed method and a reference analytical technique, namely ion chromatography.

More recently, Hattori et al. (2025) investigated the dynamics of blood lactate and sweat lactate following high-intensity exercise. Sweat lactate was continuously monitored during exercise and recovery using a wearable electrochemical sensor (Grace Imaging, Japan), whereas capillary blood lactate samples were collected from the fingertip at rest and at multiple time points following exercise (0.5, 2, 5, 10, 15, 20, 25, and 30 minutes) using a lactate analyzer (Arkray, Japan). A temporal alignment was observed between the second peak of sweat lactate and the peak of blood lactate. However, correlations based solely on peak values did not reach statistical significance, which the authors attributed to the limited sample size. Consequently, an additional analysis was performed using continuous time-series data, revealing strong Pearson correlations between sweat and blood lactate concentrations ($r = 0.501–0.933$; $p < 0.001$). Regression analysis conducted using the same continuous dataset demonstrated that sweat lactate, when considered together with sweat rate, could predict blood lactate levels with high accuracy.

Although Cinca-Morros et al. (2024) emphasized the apparent contradictions among the findings reported in studies investigating lactate and other sweat analytes, the work of Hattori et al. (2025) suggests that meaningful correlations between these biomarkers may emerge when appropriate analytical approaches are employed.

II. Glucose

Glucose is widely recognized as a key biomarker for diabetes; however, its continuous monitoring is also highly relevant for other applications, including the assessment of energy availability, the monitoring of fatigue in athletes, and the prevention of renal complications (Dai, Lu, & Zhou, 2025; Promphet et al., 2025).

According to Lu et al. (2025), the physiological correlation between sweat and blood glucose levels is notably weak and variable. Nevertheless, recent efforts have focused on developing strategies to improve this relationship. In this context, one study evaluated an integrated sensor for sweat glucose detection in ten healthy human volunteers. Sweat production was induced through a light exercise session performed 30 minutes before and after meals. In parallel, blood glucose levels were monitored using a commercial glucometer. Sweat and blood glucose concentrations exhibited a strong linear correlation, with coefficients ranging from 0.96 to 0.97 across all ten participants (Meng et al., 2025).

Another study, which investigated the consumption of meals with different carbohydrate loads, focused on the simultaneous measurement of glucose signals in sweat and blood. The sweat glucose profiles closely followed the fluctuations observed in blood glucose levels (Yang et al., 2025).

A device developed by Peringeth et al. (2025) performed measurements every 30 minutes to determine sweat glucose concentration. Simultaneously, a portable blood glucose monitoring system was used to measure blood glucose concentrations. Although a delay was observed in the readings obtained from the sweat-analysis device, the sweat glucose data showed a strong correlation with blood glucose concentrations.

In contrast, Saha et al. (2024) reported different findings. The researchers developed a platform for monitoring sweat glucose in five healthy volunteers and three individuals with diabetes. The platform combined osmotically active hydrogels with enzymatic biochemical sensors. Measurements were performed on the fingertips and forearm, the latter being the same anatomical site selected by Peringeth et al. (2025). However, the correlations obtained were weak, suggesting that the choice of the analytical system and/or calibration method may directly influence the final results.

III. Amino Acids

Amino acids serve as the building blocks of proteins and play an important role in metabolic profiling, as well as in the identification of biomarkers for metabolic disorders and the monitoring of therapeutic responses to these conditions (Spano et al., 2025). In a study investigating the potential use of sweat amino acids as biomarkers, amino acid concentrations in sweat were measured and compared with their corresponding concentrations in the bloodstream. Among the 15 amino acids evaluated, significant correlations were observed only for valine, alanine, and threonine, with Pearson correlation coefficients (ρ) of 0.49, 0.63, and 0.63, respectively. According to the authors, the molecular weight of the amino acids appeared to influence their partitioning into sweat (Spano et al., 2025).

IV. Cortisol

Cortisol is a hormone secreted by the adrenal gland in response to physiological and/or psychological stress (Kraemer et al., 2005). Therefore, cortisol represents an important biomarker for stress assessment. Systematic studies conducted in both laboratory settings and human volunteers have demonstrated the main characteristics and capabilities of sweat-based monitoring systems, as well as strong correlations between cortisol levels in sweat, blood serum, and saliva (Bandodkar, Ghaffari, & Rogers, 2020). Messina et al. (2025) reported that sweat cortisol follows the circadian fluctuations observed in serum cortisol, exhibiting a correlation coefficient of 0.87.

V. Uric Acid

Uric acid is a non-enzymatic biomarker whose elevated blood levels are clinically associated with the pathogenesis of gout (Yang et al., 2025). Its presence in sweat and its correlation with blood levels were investigated by Yang et al. (2025). In this study, a baseline level was established through the simultaneous measurement of uric acid in sweat and blood samples collected from fasting volunteers.

The participants were then subjected to a diet rich in foods known to significantly increase uric acid levels in the body. Continuous monitoring was performed over an 8-hour period. At the end of the monitoring session, one participant exhibited a correlation coefficient of 0.875 between sweat and blood uric acid levels. However, no information was provided regarding the remaining participants, making it difficult to assess the overall consistency and reproducibility of the study findings.

VI. Creatinine

Blood plasma creatinine concentrations are strongly associated with renal dysfunction and are therefore useful biomarkers for guiding hemodialysis in patients with end-stage renal disease (Adelaars et al., 2024).

In an investigation involving four volunteers, creatinine levels in sweat, which were successfully detected in all participants, followed the same trends observed in blood concentrations measured using standard laboratory methods, exhibiting a high correlation ($R^2 = 0.9823$) (Promphet et al., 2025).

A study conducted by Adelaars et al. (2024), involving a larger population of 40 participants, reported different findings. The methodology consisted of measuring creatinine concentrations in sweat and blood at the beginning and end of a hemodialysis session. The results revealed a correlation coefficient of 0.58, substantially lower than that reported by Promphet et al. (2025), suggesting that the number of participants included in the analysis may influence the observed correlation.

VII. Myo-Inositol

Myo-inositol, which is essential for several vital physiological processes, including cell growth and survival, is an important biomarker associated with multiple pathological conditions, such as mental disorders, metabolic diseases, and kidney disorders. Recently, a study investigated the effects of oral

myo-inositol administration in healthy individuals (Deng, Bai, & Zhou, 2025).

The results demonstrated similar trends between myo-inositol concentrations in sweat and plasma, as well as a strong correlation between the two matrices (r = 0.901).

VIII. Urea

Urea, similarly to creatinine, is a biomarker strongly associated with renal dysfunction and has therefore been extensively investigated for applications related to the monitoring of kidney disorders. In this context, Laochai et al. (2024) developed a potentiometric sensor that demonstrated a high correlation (R^2 = 0.974) between urea levels measured in sweat collected from the fingertips and values obtained using a commercial blood urea meter. The study was conducted with eight volunteers.

The study by Adelaars et al. (2024), previously discussed, also included analyses involving urea. For this biomarker, a correlation coefficient of 0.77 was observed, further suggesting that sample size may be an important factor influencing the results obtained.

VIII. Other biomarkers

In addition to the biomarkers discussed above, several others have demonstrated significant correlations between their concentrations in sweat and blood across different studies. In 2024, Davis et al. reported correlations between sweat and blood concentrations of pro-inflammatory cytokines, including interleukin-6 (IL-6) and tumor necrosis factor-alpha (TNF-α), as well as C-reactive protein (CRP). These findings highlighted the potential of sweat analysis for investigating the progression of cirrhosis.

Correlations between different biomarkers measured in sweat and blood have also been reported. Studies indicate that the production and metabolism of DL-lactic acid (DL-LA), a racemic mixture of the enantiomers of lactic acid, are associated with diabetes mellitus. In this context, Jin et al. (2024) evaluated the correlation between the DL-LA ratio in sweat and fasting plasma glucose levels in individuals with diabetes. The results demonstrated a moderate positive correlation between these biomarkers, indicating that sweat analysis is promising not only for investigating correlations involving the same biomarker across different biofluids, but also for exploring relationships between distinct biomarkers.

Table 1 summarizes the studies included in this review that reported correlations between biomarkers measured in sweat and their corresponding blood biomarkers.

IX. Factors influencing sweat–blood correlations

Several methods can be used to induce sweating, including physical exercise, environmental conditions such as temperature and relative humidity, and exposure to xenobiotics, such as pilocarpine. Evidence suggests that non-physiological methods of sweat induction, particularly those involving pilocarpine administrations, may negatively affect the final concentrations of analytes in sweat because they do not accurately replicate real-world physiological conditions. This effect appears to be especially relevant for amino acids (Spano et al., 2025).

Exercise intensity also influences the correlation between biomarkers measured in blood and sweat, as observed for lactate. Saha et al. (2021) found that under conditions of low physical exertion, lactate concentrations in blood and sweat exhibited poor correlation. In contrast, when participants exceeded the lactate threshold, a strong correlation between blood and sweat lactate concentrations was observed.

Spano et al. (2025) further emphasized the need to better understand the extent to which analyte concentrations in sweat truly reflect secretion by sweat glands. It is also important to elucidate the mechanisms governing the transport of analytes from the interstitial fluid, the precursor of sweat, into the sweat ducts. As noted by Childs et al. (2024), the molecular size of compounds present in interstitial fluid may restrict this transfer. Accordingly, the authors recommend additional in vitro studies using intact sweat glands to improve the understanding of these mechanisms.

In addition to the method of sweat induction, appropriate skin preparation and thorough cleansing of the collection site are critical considerations, as the skin may act as a source of sample contamination, leading to inconsistent or incongruent data (Dai, Lu, & Zhou, 2025). Furthermore, variations in sweat rate and composition, pH fluctuations, and differences in sweat gland activity are associated with a wide range of factors, including sex, ethnicity, age, physical fitness level, exercise intensity, anatomical collection site, and methodological aspects. These factors contribute to the complexity of the observed correlations, which do not always exhibit a direct and proportional relationship with blood concentrations (Yang et al., 2025; Cinca-Morros et al., 2024; Klous et al., 2021).

In this context, inconsistencies have also been reported regarding the correlation between sweat and blood lactate levels during short-duration, high-intensity exercise. These discrepancies may result from local lactate production by sweat glands as well as from the dilution effects previously described (Hattori et al., 2025).

Table 1. Biomarkers and their corresponding correlation coefficients. Adapted from Childs et al. (2024)

Title	Reference	Reference Biofluid	Analyte	Correlation Coefficient
Investigation of effects of collection conditions on amino acid concentrations in sweat and correlations with their Circulating levels in plasma	Spano et al., 2025	Plasma	Valine Alanine Threonine	0.49 0.63 0.63
Nanostructure-gated organic electrochemical transistors for accurate glucose monitoring in dynamic biological pH conditions	Meng et al., 2025	Blood	Glucose	0.97 ou 0.96
A miniaturized battery-free wireless epidermal platform for multiplexed sweat biomarker monitoring	Yang et al., 2025	Blood	Uric Acid	0.87
Non-invasive fingertip sweat biosensor for early kidney disease biomarker screening	Promphet et al., 2025	Blood	Creatinine Glucose	0.98 0.93
Skin-Interfaced Entirely Self-Contained Wearable Biosensor for the Noninvasive and Dynamic Monitoring of Sweat Myo-Inositol	Deng; Bai; Zhou, 2025	Plasma	Myo-inositol	0.90
Short Report: Estimating Blood Lactate Dynamics from Sweat Lactate and Sweat Rate After HighIntensity Exercise – A Pilot Regression-Based Study	Hattori et al., 2025	Blood	Lactate	0.93
A Passive Perspiration Inspired Wearable Platform for Continuous Glucose Monitoring	Saha et al., 2024	Blood	Glucose	0.67 a 0.94
Diving into Sweat: Advances, Challenges, and Future Directions in Wearable Sweat Sensing	Childs et al., 2024	Blood	Estradiol Cholesterol Ethanol Vitamin C	0.837 0.95 (before food intake) 0.92 (after food intake) 0.95 a 0.97 0.81 a 0.72
A dried sweat spot paper (DSSP) method based on novel mass spectrometry probe labeling for detection and resolution of DL-lactate enantiomers as potential biomarkers for diabetes mellitus	Jin et al., 2024	Blood	DL-Lactic Acid (sweat) and Glucose (blood)	0.77
Touch–based potentiometric sensors for simultaneous detection of urea and ammonium from fingertip sweat	Laochai et al., 2024	Blood	Urea	0.97
The correlation of urea and creatinine concentrations in sweat and saliva with plasma during hemodialysis: an observational cohort study	Adelaars et al., 2024	Plasma	Urea Creatinine	0.77 0.58
Fully Integrated Wearable Device for Continuous Sweat Lactate Monitoring in Sports	Xuan et al., 2023	Blood	Lactate	0.81
A novel sweat sensor detects inflammatory differential rhythmicity patterns in inpatients and outpatients with cirrhosis	Davis et al., 2024	Serum	TNF-α CRP IL-6	0.94 0.66 0.48
Advances in Electrochemical Nanobiosensors for Noninvasive Stress Biomarker Detection	Messina et al., 2025	Serum	Cortisol	0.87
Wearable Hydrogel SERS Chip Utilizing Plasmonic Trimers for Uric Acid Analysis in Sweat	Li et al., 2024	Serum	Uric acid	0.95
A skin-interfaced sensor for noninvasive monitoring of pharmacokinetic and pharmacodynamic responses	Zheng et al., 2026	Plasma	Metformin	0.79

Conclusion

The studies analyzed indicate that there are indeed correlations between analytes present in sweat and blood; however, this field is still in a consolidation phase, characterized by significant gaps and specific challenges related both to the biofluid and its analytes. Given the relevance of continuous and real-time physiological monitoring and the potential of sweat in this context, it is essential to establish rigorous methodological

procedures grounded in a solid theoretical understanding of the physiological aspects of this biofluid. Superficial methodological approaches may lead to misleading results and increase uncertainty in a field that requires high precision; conversely, a deeper understanding of sweat gland characteristics and the complex composition of sweat may enable the development of more robust and reliable methods, capable of more consistently elucidating the relationship between sweat and blood in the human body.

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