Urolithiasis (2024) 52:132
https://doi.org/10.1007/s00240-024-01630-y

REVIEW

Non-invasive approaches to hydration assessment: a literature review

Achraf Tahar[1] · Hadil Zrour[1] · Stéphane Dupont[2] · Agnieszka Pozdzik[3,4]

Received: 3 September 2024 / Accepted: 9 September 2024 / Published online: 26 September 2024

Abstract

Traditional hydration assessment methods, while accurate, are often invasive and impractical for routine monitoring. In response, innovative non-invasive techniques such as bioelectrical impedance analysis (BIA), electrodermal activity (EDA), electrocardiogram (ECG) monitoring, and urine color charts have emerged, offering greater comfort and accessibility for patients. These methods use various types of sensors to capture a range of bio-signals, followed by machine learning-based classification or regression methods, providing real-time feedback on hydration status, which is crucial for effective management and prevention of urinary stones. This review explores the principles, applications, and efficacy of these non-invasive techniques, highlighting their potential to transform hydration monitoring in clinical and everyday settings. By facilitating improved patient compliance and enabling proactive hydration management, these approaches align with contemporary trends in personalized healthcare. This article presents a literature review on non-invasive approaches to hydration assessment, focusing on their significance in preventing kidney stone disease and enhancing kidney health.

Keywords Kidney stones · Water intake · Mobile application · Smart bottle

Abbreviations

BIA	Bioelectrical impedance analysis
EDA	Electrodermal activity
ECG	Electrocardiogram
KSD	Kidney stone disease
R	Resistance
ECW	Extracellular water
Xc	Reactance
ICW	Intracellular water
GSR	Galvanic skin response
BiLSTM	Bidirectional long short-term memory
K-NN	K-nearest neighbors
MMD	Monitoring my dehydration
HRV	Heart rate variability
BE	Before exercise
PE	Post-exercise
PH	After hydration
SDRR	Standard deviation of RR intervals
RMSSD	Root mean square of successive RR interval differences
SVM	Support vector machine
EPS	Electric potential sensing
BMI	Body mass index
HM	Hydration monitor
PPG	Photoplethysmography
DBM	Dehydration body monitor

✉ Achraf Tahar
achraf.tahar.ai@gmail.com

✉ Agnieszka Pozdzik
agapozdzik@gmail.com

Hadil Zrour
hzrour@renalcare.eu

Stéphane Dupont
stephane.dupont@umons.ac.be

1 Department of Research, Development and Innovation, Renal Care and Research Srl, Rue Saint Martin 35, 1457 Walhain, Nil Saint Vicent, Belgium

2 Artificial Intelligence Research Unit (MAIA), Department of Computer Science, University of Mons, Avenue Maistriau15, 7000 Mons, Belgium

3 Kidney Stone Clinic, University Hospital Brugmann, Place A. Van Gehuchtenplein 4, 1020 Brussels, Belgium

4 Faculty of Medicine, Université Libre de Bruxelles (ULB), Route de Lennik 808, 1070 Brussels, Belgium

Introduction

Urolithiasis, commonly known as kidney stone disease (KSD), represents a significant global health concern, with prevalence rates varying considerably across different regions. In North America, the incidence ranges from 7 to 13% of the population, while Europe sees rates between 5 and 9%. Asia, by comparison, reports lower but still substantial rates of 1% to 5% [1]. These statistics underscore the widespread nature of this condition and highlight the need for effective prevention and management strategies [2, 3].

The formation of Kidney stones is a complex process influenced by multiple factors, including genetics, diet, lifestyle, and environmental conditions [4]. However, one of the most crucial and modifiable risk factors is hydration status. Proper water intake plays a pivotal role in both the prevention and management of kidney health and disease [5, 6]. For individuals with a history of kidney stones, maintaining adequate water intake is not merely beneficial—it is an essential component of their health regimen [7].

The mechanism by which hydration helps prevent stone formation is multifaceted. Primarily, increased fluid intake leads to higher urine volume, which in turn dilutes the concentration of stone-forming constituents such as calcium, oxalate, and uric acid. This dilution effect reduces the likelihood of these substances reaching supersaturation levels and precipitating to form crystals. Additionally, proper hydration supports overall kidney function by facilitating the efficient filtration and excretion of waste products, maintaining urine pH balance, and promoting regular urination which helps flush out potential stone-forming materials [8].

Moreover, adequate hydration has benefits that extend beyond stone prevention. It aids in maintaining proper blood pressure [9], regulating body temperature [10], and supporting various metabolic processes [11]. For stone formers, the importance of hydration cannot be overstated, as recurrence rates for kidney stones can be as high as 50% within five years of the initial episode if preventive measures are not taken [12].

Despite the clear importance of hydration in urinary stone management, effectively monitoring hydration levels has long presented a challenge in clinical settings [13]. The ability to accurately assess a patient's hydration status is crucial for tailoring preventive strategies and evaluating their effectiveness. This challenge has spurred research into various methods of hydration assessment, ranging from traditional techniques to cutting-edge technologies.

Traditionally, healthcare providers have relied on well-established methods to assess dehydration. These include hematological indices such as the concentration of blood haematocrit, serum osmolality, and plasma osmolality. More advanced techniques like isotope dilution methods have also been employed [13]. While these approaches offer high accuracy and have been the gold standard for many years, they come with significant drawbacks that limit their practicality for routine use, especially in outpatient settings.

Many of these traditional methods require blood draws or other invasive procedures, which can be uncomfortable for patients and may deter regular monitoring. They often necessitate sophisticated and costly equipment, typically available only in hospital laboratories or specialized clinics. This restriction means that these tests cannot be performed at home or in many primary care settings, limiting their accessibility. Furthermore, these methods often have long turnaround times, sometimes taking hours or even days to provide results. This delay significantly limits their usefulness for frequent monitoring or for making real-time adjustments to hydration strategies [14, 15].

In response to these limitations, recent years have witnessed the emergence of novel, non-invasive approaches to hydration assessment [14–31]. These innovative methods represent a paradigm shift in how we approach hydration monitoring, offering several advantages over their traditional counterparts. They are generally more comfortable for patients, eliminating the need for blood draws or other invasive procedures. This increased comfort level can lead to better patient compliance with regular monitoring, a crucial factor in long-term stone prevention strategies [14, 32].

Moreover, many of these new techniques are designed for convenience and ease of use, making them suitable for everyday monitoring outside of clinical settings. This shift towards patient-centric, home-based monitoring aligns with broader trends in healthcare towards personalized medicine and patient empowerment [33]. By providing individuals with tools to monitor their own hydration status, these methods have the potential to improve adherence to hydration recommendations and enable more proactive management of stone risk.

Another significant advantage of these novel approaches is their ability to provide results more quickly than traditional methods. Some technologies offer real-time or near-real-time feedback on hydration status, allowing for immediate adjustments to fluid intake [27]. This rapid feedback loop can be particularly beneficial for individuals trying to optimize their hydration habits or for those at high risk of stone formation.

As we delve deeper into these innovative methods, it becomes clear that they represent not just incremental improvements but potentially transformative approaches to hydration assessment and urinary stone prevention [34, 35]. From bioelectrical impedance analysis to urine color charts, from wearable devices to smartphone apps, the landscape of hydration monitoring is evolving rapidly [14–31]. Each of these methods brings its own set of advantages and limitations, and understanding their principles, applications, and efficacy is crucial for healthcare providers and patients alike.

In this literature review, we will explore these novel approaches in detail, examining their underlying principles, practical applications, and the evidence supporting their use. We will also consider how these methods compare to traditional techniques and discuss their potential impact on the future of urinary stone management and prevention. We will also highlight remaining challenges and formulate recommendations for future research.

Search strategy

Given the diverse methods utilized in non-invasive hydration assessment, we opted for a narrative review rather than a systematic review or meta-analysis [36]. While systematic reviews offer rigorous and methodical evaluation, a narrative approach provides greater flexibility to explore and interpret the literature in a more nuanced way. This method allowed us to contextualize and reflect on hydration testing practices, offering insights that extend beyond the constraints of strict inclusion and exclusion criteria [13].

To gather relevant literature for this narrative review, we searched Google Scholar and PubMed using keywords such as “hydration,” “dehydration,” “hypohydration,” “body water,” “assessment,” “testing,” “non-invasive,” and “measurement.” We also examined the reference lists of the selected papers to discover additional relevant sources.

Non-invasive approaches

Non-invasive methods for the assessment of dehydration are innovative techniques that evaluate an individual's hydration status without resorting to invasive procedures such as blood draws or urine sampling. These approaches utilize a variety of physiological, optical, or electronic measurements to infer hydration levels based on external indicators. By providing a safe, comfortable, and convenient means of monitoring hydration, these methods are particularly valuable for everyday health assessments [32, 37].

The development of non-invasive hydration assessment techniques has been driven by the need for quick, reliable, and user-friendly methods that can be easily implemented in various settings. These methods aim to overcome the limitations of traditional invasive techniques, which can be time-consuming, uncomfortable for patients, and sometimes impractical for frequent monitoring. These methods often employ advanced technologies such as specialized sensors, wearable devices, or smartphone applications to collect and analyze data. The goal is to provide accurate, real-time information about an individual's hydration status that can be easily interpreted by both healthcare professionals and the wider community.

We'll explore non-invasive hydration assessment methods, examining their principles, advantages, and limitations. This overview will provide insight into current techniques and future possibilities in this field.

Bioimpedance analysis (BIA)

The bioimpedance analysis (BIA) is a non-invasive technique used to measure dehydration by assessing the electrical impedance of body tissues. It operates on the principle that the body's water content affects the flow of a low-level electrical current, with resistance (R) primarily reflecting extracellular water (ECW) and reactance (Xc) indicating intracellular water (ICW) [38]. By analyzing impedance values, BIA can differentiate between hydration levels; for instance, dehydration typically results in increased resistance and decreased reactance due to reduced total body water [39]. Figure 1 illustrates one of the commonly used configurations of Bioimpedance Analysis (BIA) for assessing hydration [40].

Researchers from Hamad Bin Khalifa University and Queen's University [16] have developed a bioimpedance analysis (BIA) method to assess hydration levels non-invasively. The study involved creating and simulating a model of human skin to explore how different frequencies affect skin's dielectric properties and impedance measurements. Two interdigitated electrode designs were tested, with the rectangular design showing promising results in measuring hydration levels. Researchers from the U.S. Army Research Institute of Environmental Medicine and Georgia Institute of Technology [17] explored the use of bioelectrical impedance analysis (BIA) as a reliable method for estimating changes in hydration status. Their study, published in the International Journal of Sports Medicine, highlights the effectiveness of BIA in monitoring hydration levels, which is crucial for optimizing performance and health in various settings, particularly in sports and military environments. The authors emphasize the importance of accurate hydration assessment

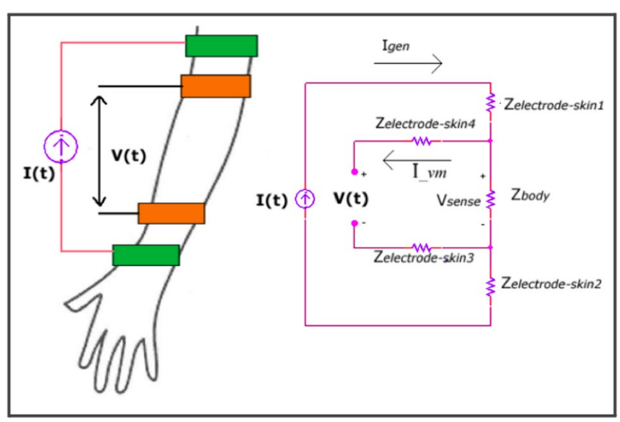

Fig. 1 Tetra polar configuration commonly used for hydration assessment [40]. The tetra polar configuration is a commonly used method in bioelectrical impedance analysis for assessing hydration status and body composition. It involves placing four electrodes on the skin to pass a small electrical current through the body. The resistance to this current, which varies with the body's water content, is then measured

to prevent dehydration-related issues and enhance overall physical performance.

The use of bioimpedance analysis is especially advantageous in clinical settings because it offers a rapid and objective evaluation of hydration status, surpassing traditional methods. This makes it particularly effective for detecting dehydration in diverse populations, with a notable emphasis on kidney stone patients. However, it is important to consider the limitations of bioimpedance analysis, such as the potential for inaccuracies caused by factors like body composition, hydration status, and electrolyte imbalances.

Electrodermal activity (EDA)

The electrodermal activity (EDA), also known as galvanic skin response (GSR), is a non-invasive technique for assessing hydration status by measuring the skin's electrical properties, which change with sweat gland activity and moisture levels. This method is based on the principle that dehydration alters sweat production and skin hydration, impacting the skin's electrical conductance. The eccrine sweat glands [41] shown in Fig. 2, controlled by the sympathetic nervous system and primarily located in the dermis, play a crucial role in this process. Dehydration leads to complex physiological changes, including variations in sweat gland activity, skin moisture content, electrolyte concentrations in sweat, and cutaneous blood flow, all of which affect the skin's electrical conductance. EDA measurements are taken by applying a weak electrical current through electrodes placed on the skin, typically on the palms or fingers [18–20].

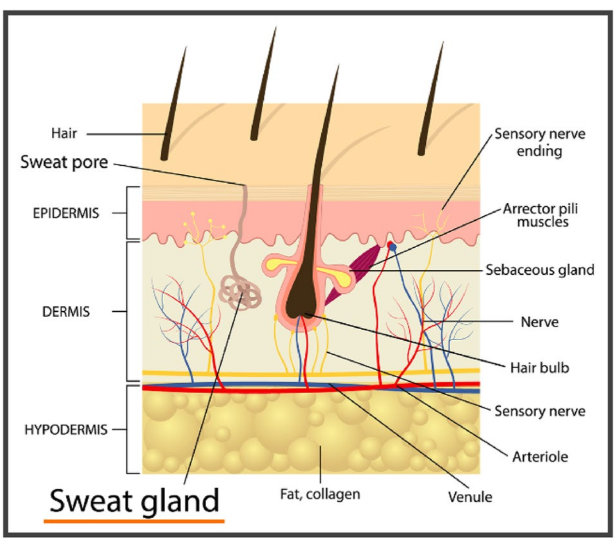

Fig. 2 A section of the human skin and an example of The eccrine sweat gland [41]. Human skin is composed of three main layers: the epidermis, dermis, and hypodermis. The eccrine sweat gland, located within the dermis, is a simple, coiled tubular structure that produces sweat and secretes it directly onto the skin's surface through a pore. This gland plays a vital role in thermoregulation and maintaining fluid balance

In a study [18], researchers developed a non-invasive system for dehydration assessment using electrodermal activity (EDA) measurements. The study involved 16 participants who were monitored in three hydration states: hydrated, mildly dehydrated (after 8 h of fluid restriction), and extremely dehydrated (after 16 h of fluid restriction). Data was collected using an EDA sensor [42] shown in Fig. 3 and the BITalino toolkit. Measurements were taken in three body postures: sitting, standing, and walking. This approach allowed for data collection across different positions that might affect EDA readings. The researchers extracted statistical features from the EDA data. These features were then used as input for a hybrid bidirectional long short-term memory (BiLSTM) neural network model. BiLSTM is a type of recurrent neural network capable of processing sequential data. The system achieved an accuracy of approximately 97% in distinguishing between the three hydration states. In another research from the University of Glasgow [20], researchers developed a machine learning-based solution for the non-invasive auto-estimation of human hydration levels using galvanic skin response (GSR). The study considered various body postures (sitting and standing) and distinct hydration states (hydrated and dehydrated) during the data collection and analysis phases. Six different machine learning algorithms were trained using real GSR data, and their performance was compared for different parameters such as window size and feature combinations. The results showed that a simple algorithm like k-nearest neighbors (K-NN) outperformed other algorithms, achieving an accuracy of up to 87.7% in correctly estimating the hydration level. Researchers from the University of Massachusetts Lowell [19] developed a dehydration self-monitoring tool called monitoring my dehydration

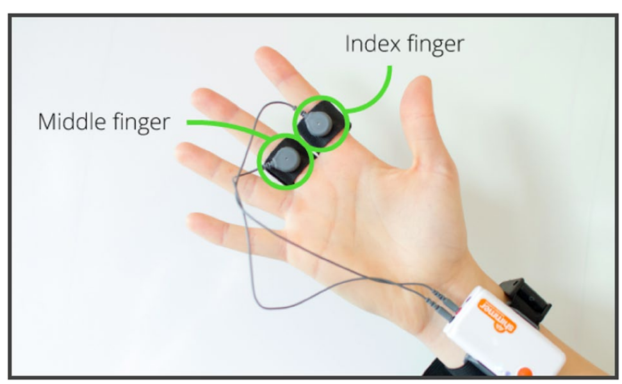

Fig. 3 An example of an electrodermal activity sensor [42]. An electrodermal activity sensor is a device used to measure the skin's electrical conductance. It typically involves two electrodes placed on the skin, often on the fingers or palm, which detect small changes in conductivity due to fluctuations in sweat gland activity

(MMD) that uses wearable electrodermal activity (EDA) sensors, signal processing, and machine learning. The tool can continuously track users' hydration levels and provide real-time alerts before dehydration impacts their health. The system achieved 84.5% accuracy, 87.5% sensitivity, and 90.3% specificity in estimating hydration levels (well-hydrated, hydrated, dehydrated, very dehydrated) across 5 recruited users. The varying accuracies achieved by these studies suggest that combining EDA measurements with a machine learning model can effectively assess hydration status non-invasively under the specific conditions of each investigation. However, it is important to acknowledge that each study employed a distinct methodology and had a limited sample size. Further research is needed to confirm the generalizability of these findings across different populations and conditions.

A significant challenge in using electrodermal activity (EDA) to assess dehydration in the human body is its sensitivity to various stimuli affecting the nervous system [43]. These stimuli include emotional states like happiness or fear, as well as environmental factors such as humidity and temperature. Both internal and external stimuli can cause rapid fluctuations in skin conductance, which can obscure the more gradual changes associated with hydration levels. Currently, there is no definitive solution to effectively isolate hydration-related EDA changes from these confounding factors, making it difficult to rely solely on EDA for accurate dehydration assessment.

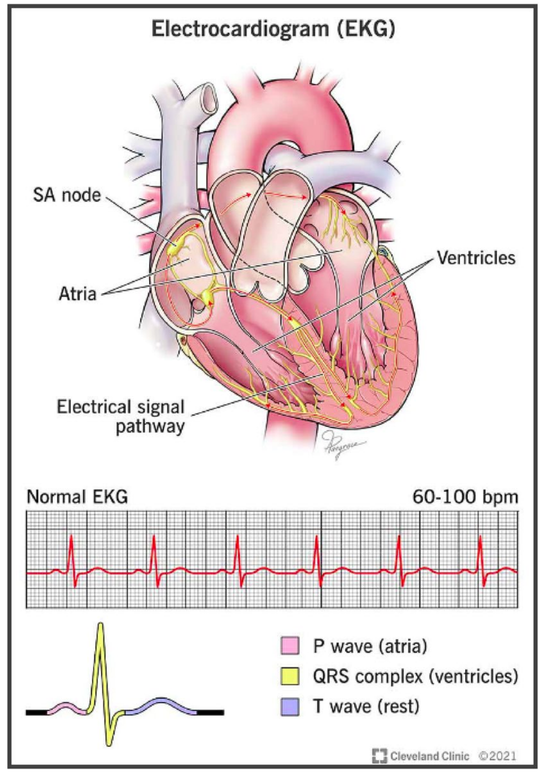

Fig. 4 Electrocardiogram showing heartbeat frequency and duration [44]. An electrocardiogram captures the heart's electrical activity, presenting it as a series of waves that illustrate both the frequency and duration of heartbeats. The frequency, expressed in beats per minute (BPM), indicates how often the heart beats, while the duration measures the time each phase of the heartbeat cycle takes. By analyzing the different components of the EKG wave, such as the P wave, QRS complex, and T wave, the heart's rhythm and overall function can be evaluated

Electrocardiogram (ECG or EKG)

The electrocardiogram (ECG or EKG) [44] explained in Fig. 4, is a non-invasive diagnostic tool that records the heart's electrical activity and has shown potential for assessing hydration status by analyzing change in heart rate variability (HRV) and other cardiac parameters influenced by fluid balance. Dehydration can lead to reduced blood volume, causing the heart to work harder and resulting in detectable ECG changes, such as decreased HRV and alterations in the QT interval.

In a new study [21], researchers explored the potential of using heart rate variability (HRV) parameters derived from electrocardiographic (ECG) signals to detect dehydration in athletes. The investigation involved 16 athletes who underwent a rigorous three-stage dehydration protocol: rest before exercise (RE), post-exercise (PE), and after hydration (PH). During each stage, ECG data were collected for 10 min, allowing for the calculation of three specific time-domain HRV parameters: RR-interval (The time between successive R-waves, which are the largest waves in the QRS complex), standard deviation of RR intervals (SDRR), and root mean square of successive RR interval differences (RMSSD). These parameters were chosen for their known sensitivity to autonomic nervous system changes, which can be affected by hydration status. The study employed two distinct machine learning techniques to classify the dehydration stages: support vector machine (SVM) and k-means clustering. SVM, a supervised learning method, was used to create a model that could distinguish between the three stages based on the HRV parameters. K-means, an unsupervised learning algorithm, was applied to see if it could naturally group the data into clusters corresponding to the dehydration stages without prior labeling. Results indicated that SVM outperformed k-means in classifying the dehydration stages, suggesting that the supervised approach was more effective for this particular application. Among the HRV parameters, the RR-interval emerged as the most effective for categorizing dehydration stages, achieving accuracy, precision, and recall scores above 0.60 when used with the SVM method. This finding highlights the particular sensitivity of the RR-interval to hydration-related changes in cardiac function. The superior performance of SVM over k-means could be attributed to its ability to handle complex, non-linear relationships in the data, which may be particularly relevant when dealing with physiological parameters that can be influenced by multiple factors. The study's results indicate that machine learning approaches, particularly supervised methods like SVM, can utilize ECG-derived HRV parameters for dehydration assessment in athletes. A study conducted by researchers from the University of Sussex [22] explored the use of electric potential sensing (EPS) technology to assess human hydration levels. The research employed a non-invasive, capacitive EPS sensor to measure the electric field generated by the human body, with a focus on cardiac electrical activity. The study examined the potential correlation between QRS amplitude in the ECG signal and hydration levels. Data collected from six subjects showed changes in QRS amplitude corresponding to periods of dehydration and subsequent hydration. The researchers observed variations among subjects, which they attributed to factors such as body mass index (BMI) and individual physiological differences. The study suggests that EPS sensor technology may have potential applications in hydration monitoring, offering a non-invasive approach. A group of researchers from Stanford University, led by Anthony Kaveh and Wayne Chung [23], have developed a machine learning system to classify hydration status using electrocardiogram (ECG) data. This method aims to detect hypohydration without traditional blood analysis tests by leveraging single-lead ECG signals. The system employs support vector machines (SVM) and extracts features from both time and spectral domains of the ECG signal, utilizing a discrete wavelet transform to filter noise and identify significant waveform characteristics. Tested on the MIT-BIH PhysioNet database, the system achieved high sensitivity (96.3%) and moderate specificity (57.9%), with a positive predictive value of 61.9% and a negative predictive value of 95.7%.

These findings have demonstrated that single-lead ECG systems can effectively classify hydration status in real-time, making it a promising method for monitoring hydration in clinical settings, athletic environments, and occupational health scenarios. However, interpreting ECG results for hydration assessment presents challenges due to confounding factors like physical activity, emotional state, circadian rhythms, and individual variability. To address these limitations, researchers often recommend combining ECG data with other physiological measures such as bioelectrical impedance analysis, skin temperature, or sweat rate monitoring. This multi-modal approach aims to enhance the accuracy of hydration assessments, potentially providing a more comprehensive picture of an individual's hydration state. As research in this field progresses, ECG-based hydration assessment, particularly when combined with advanced machine learning algorithms, may become an increasingly valuable tool in various healthcare and performance-related applications where maintaining proper hydration is crucial.

Acoustic signals

Acoustic signals for dehydration assessment utilize ultrasound technology to evaluate body hydration status by measuring the speed of sound waves traveling through muscle tissue. This method is based on the principle that the speed of ultrasound in soft tissue is directly related to the tissue's water content. When dehydration occurs, muscle water content decreases, causing an increase in ultrasound velocity. Different approaches have been developed based on this principle, enabling real-time tracking of total body water changes during conditions such as acute dehydration and rehydration in athletes. Studies have shown that this acoustic method can effectively detect abnormal hydration changes, making it a promising tool for clinical applications, especially for vulnerable populations like the kidney stone patients who are at higher risk of dehydration.

A study from Appalachian State University and Artann Laboratories Inc. [45] introduces an acoustical handheld hydration monitor (HM) designed to assess body hydration status using ultrasound velocity in muscle tissue. The HM leverages the principle that ultrasound velocity through muscle is a linear function of water content, making it a potential tool for detecting dehydration. The device was tested on healthy young adults and elderly subjects, demonstrating its ability to track changes in total body water during dehydration and rehydration, as well as day-to-day hydration variability. The results indicate that the HM could be an efficient tool for monitoring hydration status, particularly in vulnerable populations such as the elderly, infants, and athletes. Another use of acoustic signals has been proposed by researchers at Oklahoma State University who have developed AutoHydrate [24], a wearable hydration monitoring system designed to track drinking activities and daily fluid requirements. The system [46] comprises a throat microphone for collecting acoustic signals, a smartwatch for monitoring physical activity, an embedded computer for data processing, and a smartphone app for providing recommendations as shown in Fig. 5. AutoHydrate employs machine learning algorithms, specifically Support Vector Machine (SVM) for drinking activity classification and Gradient Boosting Decision Trees for body activity classification. According to the researchers, the system achieved 91.5% accuracy in drinking detection and 89.1% accuracy in body activity classification. The stated goal of AutoHydrate is to prevent health issues related to poor hydration habits by providing continuous monitoring and real-time feedback.

These studies represent different approaches to utilizing wearable technology for collecting acoustic signals and applying machine learning in hydration management, estimating either hydration level on one side, or drinking intake on the other side. However, as with all scientific research, independent replication and further testing are necessary to

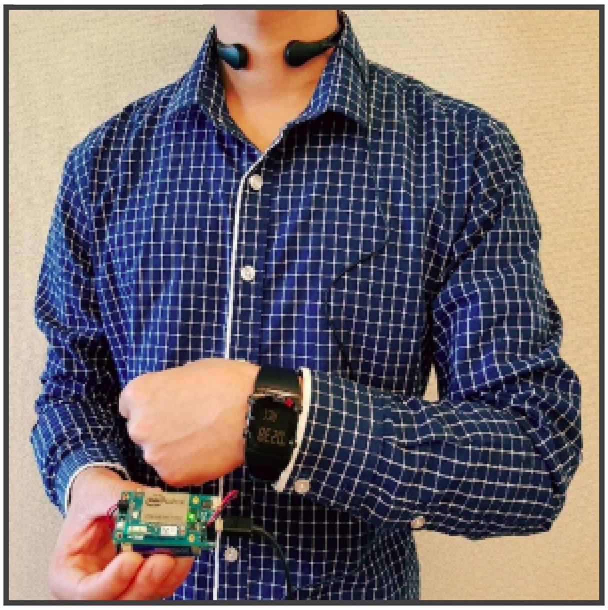

Fig. 5 The setup of the AutoHydrate System [46]. The AutoHydrate system consists of an acoustic sensor for capturing sounds from the throat, a smartwatch for monitoring body activity, and an embedded computer for gathering and analyzing the data

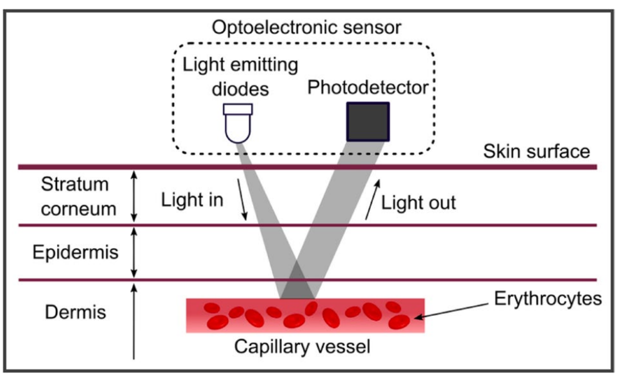

Fig. 6 Working principle of PPG sensors [48]. PPG (Photoplethysmography) sensors work by measuring changes in blood volume within the skin's microvascular tissue using light. The sensor emits light, typically from a LED, onto the skin, and a photodetector captures the light that is either absorbed or reflected by blood vessels. As blood volume fluctuates with each heartbeat, the light signal changes accordingly

fully validate their effectiveness and applicability in various real-world settings.

Photoplethysmography (PPG)

The photoplethysmography (PPG) [47, 48], shown in Fig. 6, is a non-invasive optical technique used to assess hydration status by measuring changes in blood volume and flow in peripheral tissues. This method involves emitting light, typically in the red and infrared spectrum, onto the skin and measuring the amount of light absorbed or reflected by blood vessels beneath. Hydration level fluctuations cause variations in blood volume, which in turn alters the PPG signal. Dehydration may be indicated by an increased heart rate and changes in the PPG signal amplitude, reflecting the body's compensation for reduced blood volume.

A recent research study [14] has introduced a non-invasive method for monitoring hydration levels using smartphone cameras. The technique involves recording a fingertip video to extract a photoplethysmography (PPG) signal, which reflects changes in blood volume associated with hydration status. To develop this method, researchers collected data from 25 fasting participants during Ramadan 2023, creating a labeled dataset. This data was used to train artificial intelligence models for two classification tasks: binary (hydrated or not) and four-class (fully hydrated, mildly, moderately, or extremely dehydrated) hydration assessment. The study reports that these models achieved accuracy rates between 95 and 99%. The researchers also proposed an alternative approach using high-dimensional PPG data for feature extraction and classification, interpreting results through a SHAP-based explainable AI framework. This smartphone-based hydration monitoring method is presented as a cost-effective solution that could potentially contribute to at-home health monitoring and patient-centric healthcare systems. A study realized by researchers at Ariel University [25] assessed the accuracy of a wearable hydration sensor, the dehydration body monitor (DBM), in a field trial involving 240 healthy adults. Participants wore the DBM, which utilizes photoplethysmographic and galvanic biosensors, while performing treadmill exercises. The device's output, measuring sweat loss, was compared to changes in body mass recorded by a medical balance. Results indicated a strong correlation between the DBM measurements and body mass changes, with a mean normalized root square error of approximately 2%. Bland–Altman analyses showed that less than 5% of values fell outside the 95% confidence interval, confirming the DBM's reliability for monitoring hydration, particularly in athletic and geriatric contexts. A group of researchers from the University of Connecticut and other institutions [26] developed a method for the automatic detection of dehydration using photoplethysmographic (PPG) signals collected from patients in an emergency department. By employing miniature, wearable pulse oximeters, the study analyzed changes in PPG signals to classify dehydration status through support vector machines (SVM) with a radial basis function kernel. The researchers achieved an overall classification accuracy of 67.9%, with sensitivity at 72.7% and specificity at 64.3%. These findings indicate that automatic detection of dehydration is feasible, potentially improving clinical assessments of hydration status in patients.

However, it's important to note that while PPG shows promise for hydration assessment, factors like skin pigmentation, temperature, and movement can affect signal quality. Additionally, the accuracy and reliability of PPG-based hydration monitoring may vary depending on the specific implementation and environmental conditions. Further research is needed to fully validate its effectiveness across diverse populations and real-world scenarios.

Urine color

The urine color serves as a practical indicator of hydration status, with research by Lawrence E. Armstrong highlighting its effectiveness. Armstrong developed an eight-color urine chart [51] in the late 1980s, shown in Fig. 7, which correlates urine color with hydration levels, where lighter shades indicate optimal hydration and darker shades signal dehydration. His studies demonstrated significant relationships between urine color, osmolality, and specific gravity, establishing that darker urine corresponds to higher dehydration levels. This method allows individuals to quickly self-assess hydration without specialized equipment, although it is subject to some limitations, such as environmental factors and individual variations in color perception [49, 50].

Researchers from the University of Malaya [15, 27] have conducted multiple studies exploring the use of smartphone-based urine colorimetry for assessing hydration status in dengue patients. In one study, they found strong correlations between urine color values captured by mobile phone cameras and established laboratory parameters like urine osmolality and specific gravity. In a more recent study, the researchers aimed to further evaluate the reliability of this method by comparing urine color values across different smartphone brands under various lighting conditions. They used a customized photo box with a single light source to capture urine samples using five smartphone models. Without color correction, the phones showed the best agreement for Blue and Green values under daylight lighting. However, when using a commercially available color calibration card, the study found exceptional inter-phone and intra-phone agreement for the blue and green values (ICC > 0.9) after color correction. Red values remained poorly correlated even with calibration. These findings suggest that color calibration significantly improves the reliability of smartphone urine colorimetry, positioning it as a promising point-of-care tool for hydration assessment in dengue patients. The researchers' first work demonstrated the strong correlation between smartphone-based urine color values and laboratory hydration markers. The second study builds on this by showing that color calibration enhances the consistency of urine colorimetry across different phone models and lighting conditions. Together, these studies support the feasibility of using smartphone technology for objective, non-invasive hydration monitoring in dengue patients. In another study [28], researchers investigated the validity of using a urine color chart as an indicator of hydration status among frail nursing home residents. Conducted in seven nursing homes in Iowa, the study included 98 participants aged 65 and older, excluding those with certain medical conditions. The researchers collected weekly urine samples to measure urine color and specific gravity, finding significant correlations between the two (rs = 0.3–0.7, p < 0.01). Notably, associations were stronger in females and those with adequate renal function.

These findings suggest that urine color can serve as a practical tool for monitoring hydration to help prevent dehydration-related complications. However, its accuracy may be limited by factors such as diet, medications, and individual metabolism.

Motion sensing

Motion sensing technology can assess hydration status primarily by detecting drinking gestures through wearable devices like smartwatches, which track wrist movements associated with drinking from a container.

In a research study [29] Researchers developed SipIT which is a behavioral intervention system for kidney stone patients struggling to meet fluid intake guidelines. It tracks fluid consumption automatically via a connected water bottle and smartwatch with drinking gesture detection, while also allowing manual input through a mobile app. The system

Fig. 7 E. Armstrong urine color chart [51]. The E. Armstrong urine color chart is a tool used to assess hydration status based on the color of urine. It presents a range of urine colors, from pale yellow to dark amber, with lighter colors indicating better hydration and darker colors suggesting hypohydration

Table 1 Current state of non-invasive hydration assessment techniques

Methods used for hydration status evaluation	Technologies used	Clinical advantages	Technical limitations	Clinical study
Hydration assessment using the bio-impedance analysis method [16]	Bio-impedance analysis, electrode design, bodystat multiscan	Non-invasive, real-time monitoring, wide applicability	Exclusion criteria, measurement variability	6 healthy subjects aged 18–60 participated. Results showed capacitance measurements can distinguish severe dehydration, but not minor differences in hydration levels [16]
Bioelectrical impedance to estimate changes in hydration status [17]	Bio-impedance analysis	non-invasive, simplicity and speed, reliability in euhydrated states	Confounding factors, validity in altered states	No clinical study was conducted
Personalized wearable electrodermal sensing-based human skin hydration level detection for sports, health and wellbeing [18]	Electrodermal sensing, wearable devices, data processing algorithms	Non-invasive, continuous monitoring, personalization	Environmental influence, calibration needs	16 different participants, including six females and ten males from different ethnicity groups. None of the participants has any known conditions of over hydration. Results show a recall value of 0.96, 0.96, 0.97 for the detected hydrated state, mildly dehydrated state, and extremely dehydrated state [18]
Non-invasive hydration level estimation in human body using galvanic skin response [20]	Wearable hydration sensors, capacitance measurement, electrodermal activity, wireless data transmission	Non-invasive, real-time monitoring, user-friendly design, personalization	Environmental influence, limited testing	Four males and one female of different ethnicity, all in the bracket of 25 to 30 years of age with no known conditions of edema or hypo-hydration. Participated in the study. Results show an accuracy of 87.78% [20]
Monitoring my dehydration: a non-invasive dehydration alert system using electrodermal activity [19]	Electrodermal activity, signal processing and machine learning, mobile application	Non-invasive, real-time monitoring, personalization	Limited sample size, environmental influence	5 participants with an age range of 23–35 participated in the study during the month of Ramadan. Results show an accuracy of 84.5% [19]
Machine learning methods in the classification of the athletes dehydration [21]	Electrocardiogram signals, machine learning algorithms, data collection and processing	Non-invasive, real-time monitoring, adaptability	Requirement for large datasets, interpretability	16 adults (male, age = 22.63 ± 2.13 years old) enrolled in the study. The variable that best categorized the dehydration stages was the RR-interval obtained with the SVM method with accuracy, precision and recall above 0.60 [21]
Towards the correlation between human hydration and the electrical activity of the heart using electric potential sensors [22]	Electrocardiogram signals	Non-invasive, high sensitivity	High cost, limited use	No clinical study was conducted
Classification of hydration status using electrocardiogram and machine learning [23]	Electrocardiogram signals, machine learning	Non-invasive, high sensitivity	Variability in ECG data, limited clinical application	No clinical study was conducted

Table 1 (continued)

Methods used for hydration status evaluation	Technologies used	Clinical advantages	Technical limitations	Clinical study
Acoustical method of whole-body hydration status monitoring [45]	Ultrasonic hydration monitor, ultrasound velocity measurement, data storage and connectivity	Non-invasive, real-time monitoring, high sensitivity	Dependence on muscle tissue, calibration needs, variability	82 male and female collegiate athletes and 20 elderly individuals were assessed. Results revealed an average change in ultrasound velocity of 1.1 m/s per 1% of body weight lost [52]
AutoHydrate: a wearable hydration monitoring system [24]	acoustic signals, mobile application	Non-invasive, real-time monitoring, high sensitivity	Environmental factors, calibration needs	10 healthy and normal weight participants of average age 28.2 enrolled in study. The study achieved accuracy of 91.5% for drinking activity recognition and 89.12% for body activity recognition [24]
You can monitor your hydration level using your smartphone camera [14]	Photoplethysmography, smartphone camera, machine learning	Non-invasive, cost-effective, personalization	Dependence on smartphone quality, environmental factors, dataset limitations	25 fasting subjects (16 males, 9 females) with an average age of 29.4 years, an average weight of 63 kg, and an average height of 164.23 cm participated in the study. Results show high accuracy in the range of 95% to 99% [14]
An accurate wearable hydration sensor: real-world evaluation of practical use [25]	Photoplethysmography, smartwatch integration	Non-invasive, real-time monitoring, user-friendly	Dependence on sweat composition, limited to specific activities	240 healthy adults of both sexes in different age groups were recruited. The method error for all groups studied ranged from 2.01–2.50% [53]
Automatic detection of dehydration using support vector machines [26]	Photoplethysmography, machine learning, variable frequency complex demodulation	Non-invasive, automatic detection	Classification accuracy, limited sample size	42 patients with dehydrating illnesses were enrolled in this study. The overall accuracy was 67.91%, sensitivity 72.77% and specificity 64.31% [26]
Assessing dehydration status in dengue patients using urine colourimetry and mobile phone technology [27]	Urine colorimetry, mobile application, smartphone camera	Non-invasive, cost-effective	subjective assessment, dependence on smartphone quality, influence of medications and diet, potential for misinterpretation	117 patients between the ages of 12 and 60 years with suspected or confirmed dengue fever participated in the study. Results show strong correlations between urine osmolality and the RGB of urine colour [27]
Improving the reliability of smartphone-based urine colorimetry using a colour card calibration method [15]	Urine colorimetry, mobile application, smartphone camera, color calibration card	Non-invasive, cost-effective, color calibration	Dependence on smartphone quality, influence of medications and diet, influence of lighting conditions	58 patients with probable or confirmed dengue fever based on WHO diagnostic criteria participated in the study. Results show that colour calibration using photo colour cards improved the reliability of smartphone urine colorimetry [15]

Table 1 (continued)

Methods used for hydration status evaluation	Technologies used	Clinical advantages	Technical limitations	Clinical study
Use of a urine color chart to monitor hydration status in nursing home residents [28]	Urine color chart, chemstrip mini urine analyzer	Non-invasive, simplicity and accessibility	Renal function dependency, influence of medications and diet, potential for misinterpretation	98 nursing home residents (53% female) with a mean age of 84 years participated in the study. results show a moderate to strong positive correlation between urine color and urine specific gravity [28]
Feasibility of Mini sipIT behavioral intervention to increase urine volume in patients with kidney stones [30]	Connected water bottle, mobile application, behavioral intervention framework	High engagement, increased water intake	Single-group design, short duration, complexity perception	26 Adults with a history of kidney stones and lab-verified low urine production adhered to the study. Results show a significant increase in 24-h urine volume was observed after the 1-month intervention [54]
Just-in-time adaptive intervention to promote fluid consumption in patients with kidney stones [29]	Smartwatch, connected water bottle, mobile application	High engagement, automated tracking, increased water intake	Device dependency, low accuracy	31 Adults with a history of kidney stones participated in the study. Results show a significant increase in water intake [54]
Promoting fluid intake to increase urine volume for kidney stone prevention: protocol for a randomized controlled efficacy trial of the sipIT intervention [31]	Smartwatch, connected water bottle, mobile application	Automated tracking, engaging reminders, increased water intake	Device dependency, consistency required	216 adults with a history of kidney stones and lab-verified low urine production adhered to the study. Results show a significant increase in 24-h urine volume was observed after the 1-month intervention [54]

uses just-in-time reminders and behavioral techniques to encourage increased water intake, aiming to improve hydration and potentially reduce kidney stone risk. To assess the effectiveness of this system, several clinical trials have been conducted. The first study [29] established proof-of-concept for the intervention, indicating that it reduced common barriers to fluid intake and enhanced drinking-related automaticity. The second study [30] evaluated a reduced-cost version of the intervention, called mini sipIT, which utilized only the connected water bottle and its companion mobile app for self-tracking. The results showed a significant increase in 24-h urine volume, suggesting that this technology-based behavioral intervention could effectively boost urine output in adults—a critical component of prevention guidelines associated with a reduced risk of kidney stone recurrence. The third clinical trial [31] is a randomized controlled trial designed to further investigate the impact of the sipIT behavioral intervention in kidney stone patients.

These different studies demonstrate the effectiveness of using motion sensors with connected objects like smart water bottles and smartwatches to assess hydration. However, the main challenge is ensuring the accuracy and reliability of these devices across various user demographics and environmental conditions, as well as integrating the data seamlessly into comprehensive health monitoring systems.

Concise overview of non-invasive hydration assessment technique

This section offers a concise overview of non-invasive hydration assessment techniques discussed in this literature review [14–31, 45, 52–54]. The following Table 1 summarizes key findings and methodologies, highlighting the advantages of these innovative approaches over traditional methods, their limitations, the technologies employed, and whether clinical studies have been conducted. This comprehensive analysis aims to provide a clear understanding of the current state of non-invasive hydration assessment techniques.

Conclusions and perspectives

In exploring different approaches to create systems capable of monitoring hydration non-invasively, researchers have investigated various technologies including Electrodermal Activity (EDA), Electrocardiography (ECG), Photoplethysmography (PPG), smartphone-based imaging, and Acoustic signals. Each method shows promise in providing non-invasive hydration assessment, often leveraging machine learning algorithms to improve accuracy. While initial results from many studies appear promising, with some reporting high accuracy rates, challenges remain in validating these methods across diverse populations and real-world conditions, addressing confounding factors, ensuring long-term reliability, and integrating the technologies into practical devices. As research progresses, a combination of these approaches, possibly integrated into wearable or mobile devices, could provide more comprehensive and accurate hydration monitoring. The potential impact of successful non-invasive hydration monitoring is significant, with applications in healthcare, specifically for patients with kidney disease, sports performance, occupational safety, and personal wellness. However, further large-scale trials, cross-validation of different methods, and development of standardized protocols are necessary to move these technologies towards practical implementation, while carefully considering ethical and privacy implications.

Author contributions A.T. and A.P. wrote the main manuscript text. A.T. prepared figures. All authors reviewed the manuscript.

Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest H.Z. is currently employed at Renal Care & Research. A.P. serves on the board of Renal Care & Research.

References

1. Lotan Y, Daudon M, Bruyère F, Talaska G, Strippoli G, Johnson RJ, Tack I (2013) Impact of fluid intake in the prevention of urinary system diseases: a brief review. Curr Opin Nephrol Hypertens 22:S1
2. Williams JC, Gambaro G, Rodgers A et al (2021) Urine and stone analysis for the investigation of the renal stone former: a consensus conference. Urolithiasis 49:1–16
3. Pozdzik A, Grillo V, Sakhaee K (2024) Gaps in kidney stone disease management: from clinical theory to patient reality. Urolithiasis 52:61
4. Dawson CH, Tomson CR (2012) Kidney stone disease: pathophysiology, investigation and medical treatment. Clin Med 12:467–471
5. Wang J-S, Chiang H-Y, Chen H-L, Flores M, Navas-Acien A, Kuo C-C (2022) Association of water intake and hydration status with risk of kidney stone formation based on NHANES 2009–2012 cycles. Public Health Nutr 25:2403–2414
6. Dello Russo M, Formisano A, Lauria F et al (2023) Dietary Diversity and its association with diet quality and health status of European children, adolescents, and adults: results from the I.Family study. Foods 12:4458
7. Courbebaisse M, Travers S, Bouderlique E, Michon-Colin A, Daudon M, De Mul A, Poli L, Baron S, Prot-Bertoye C (2023) Hydration for adult patients with nephrolithiasis: specificities and current recommendations. Nutrients 15:4885
8. Gamage KN, Jamnadass E, Sulaiman SK, Pietropaolo A, Aboumarzouk O, Somani BK (2020) The role of fluid intake in the prevention of kidney stone disease: a systematic review over the last two decades. Turk J Urol 46:S92–S103

9. Mohammedin AS, AlSaid AH, Almalki AM, Alsaiari AR, Alghamdi FN, Jalalah AA, Alghamdi AF, Jatoi N-A (2022) Assessment of hydration status and blood pressure in a tertiary care hospital at Al-Khobar. Cureus 14:e27706
10. Sawka MN, Latzka WA, Matott RP, Montain SJ (1998) Hydration effects on temperature regulation. Int J Sports Med 19(Suppl 2):S108-110
11. Thornton SN (2016) Increased hydration can be associated with weight loss. Front Nutr. https://doi.org/10.3389/fnut.2016.00018
12. Tamborino F, Cicchetti R, Mascitti M et al (2024) Pathophysiology and main molecular mechanisms of urinary stone formation and recurrence. Int J Mol Sci 25:3075
13. Barley OR, Chapman DW, Abbiss CR (2020) Reviewing the current methods of assessing hydration in athletes. J Int Soc Sports Nutr 17:52
14. Alaslani R, Perzhilla L, Rahman MMU, Laleg-Kirati T-M, Al-Naffouri TY (2024) You can monitor your hydration level using your smartphone camera. https://doi.org/10.48550/arXiv.2402.07467
15. Noor Azhar M, Bustam A, Naseem FS, Shuin SS, Md Yusuf MH, Hishamudin NU, Poh K (2023) Improving the reliability of smartphone-based urine colorimetry using a colour card calibration method. Digit Health 9:20552076231154684
16. AlDisi R, Bader Q, Bermak A (2022) Hydration assessment using the bio-impedance analysis method. Sensors 22:6350
17. O'Brien C, Young AJ, Sawka MN (2002) Bioelectrical impedance to estimate changes in hydration status. Int J Sports Med 23:361–366
18. Liaqat S, Dashtipour K, Rizwan A, Usman M, Shah SA, Arshad K, Assaleh K, Ramzan N (2022) Personalized wearable electrodermal sensing-based human skin hydration level detection for sports, health and wellbeing. Sci Rep 12:3715
19. Kulkarni N, Compton C, Luna J, Alam MAU (2020) Monitoring my dehydration: a non-invasive dehydration alert system using electrodermal activity. https://doi.org/10.48550/arXiv.2009.13626
20. Rizwan A, Abu Ali N, Zoha A, Ozturk M, Alomaniy A, Imran M, Abbasi Q (2020) Non-invasive hydration level estimation in human body using galvanic skin response. IEEE Sens J. https://doi.org/10.1109/JSEN.2020.2965892
21. Alvarez A, Severeyn E, Velásquez J, Wong S, Perpiñan G, Huerta M (2019) Machine learning methods in the classification of the athletes dehydration. In: 2019 IEEE Fourth Ecuad. Tech. Chapters Meet. ETCM. pp 1–5
22. Rendon-Morales E, Roggen D, Prance H, Prance RJ (2015) Towards the correlation between human hydration and the electrical activity of the heart using Electric Potential Sensors. In: 2015 IEEE Sens. Appl. Symp. SAS. pp 1–5
23. Kaveh A, Chung W (2013) Classification of hydration status using electrocardiogram and machine learning. In: AIP Conference Proceedings (Vol. 1559, No. 1, pp. 240-249). American Institute of Physics
24. Mengistu Y, Pham M, Manh Do H, Sheng W (2016) AutoHydrate: a wearable hydration monitoring system. In: 2016 IEEERSJ Int. Conf. Intell. Robots Syst. IROS. pp 1857–1862
25. Rodin D, Shapiro Y, Pinhasov A, Kreinin A, Kirby M (2022) An accurate wearable hydration sensor: real-world evaluation of practical use. PLoS ONE 17:e0272646
26. Reljin N, Malyuta Y, Zimmer G, Mendelson Y, Blehar DJ, Darling CE, Chon KH (2018) Automatic Detection of dehydration using support vector machines. In: 2018 14th Symp. Neural Netw. Appl. NEUREL. pp 1–6
27. Chew N, Noor Azhar AM, Bustam A, Azanan MS, Wang C, Lum LCS (2020) Assessing dehydration status in dengue patients using urine colourimetry and mobile phone technology. PLoS Negl Trop Dis 14:e0008562
28. Mentes JC, Wakefield B, Culp K (2006) Use of a urine color chart to monitor hydration status in nursing home residents. Biol Res Nurs 7:197–203
29. Conroy DE, West AB, Brunke-Reese D, Thomaz E, Streeper NM (2020) Just-in-time adaptive intervention to promote fluid consumption in patients with kidney stones. Health Psychol Off J Div Health Psychol Am Psychol Assoc 39:1062–1069
30. Streeper NM, Fairbourn JD, Marks J, Thomaz E, Ram N, Conroy DE (2023) Feasibility of mini sipIT behavioral intervention to increase urine volume in patients with kidney stones. Urology 179:39–43
31. Conroy DE, Marks J, Cutshaw A, Ram N, Thomaz E, Streeper NM (2024) Promoting fluid intake to increase urine volume for kidney stone prevention: protocol for a randomized controlled efficacy trial of the sipIT intervention. Contemp Clin Trials 138:107454
32. Gray M, Birkenfeld JS, Butterworth I (2023) Noninvasive monitoring to detect dehydration: are we there yet? Annu Rev Biomed Eng 25:23–49
33. Johnson KB, Wei W, Weeraratne D, Frisse ME, Misulis K, Rhee K, Zhao J, Snowdon JL (2021) Precision medicine, AI, and the future of personalized health care. Clin Transl Sci 14:86–93
34. Scales CD, Desai AC, Harper JD et al (2021) Prevention of urinary stones with hydration (PUSH): design and rationale of a clinical trial. Am J Kidney Dis Off J Natl Kidney Found 77:898-906.e1
35. Aksenov LI, Streeper NM, Scales CD (2024) Leveraging behavioral modification technology for the prevention of kidney stones. Curr Opin Urol 34:14–19
36. Greenhalgh T, Thorne S, Malterud K (2018) Time to challenge the spurious hierarchy of systematic over narrative reviews? Eur J Clin Invest 48:e12931
37. Kamran F, Le VC, Frischknecht A, Wiens J, Sienko KH (2021) Noninvasive estimation of hydration status in athletes using wearable sensors and a data-driven approach based on orthostatic changes. Sensors 21:4469
38. Samoni S, Bonilla-Reséndiz LI (2019) Noninvasive methods of fluid status assessment in critically ill patients. Clinical Publishing, pp. 821–825.e2
39. Jaffrin MY, Morel H (2008) Body fluid volumes measurements by impedance: a review of bioimpedance spectroscopy (BIS) and bioimpedance analysis (BIA) methods. Med Eng Phys 30:1257–1269
40. Bari DS, Rammoo MNS, Aldosky HYY, Jaqsi MK, Martinsen ØG (2023) The five basic human senses evoke electrodermal activity. Sensors 23:8181
41. "Tobii Customer Portal." [Online]. Available: https://connect.tobii.com. Accessed 06 Aug 2024
42. "GSR Devices, GSR Signals, Metrics and Applications | MM." [Online]. Available: https://www.ashokcharan.com/Marketing-Analytics/bm-galvanic-skin-response.php#gsc.tab=0. Accessed 06 Aug 2024
43. Bari DS, Rammoo MNS, Aldosky HYY, Jaqsi MK, Martinsen ØG (2023) The five basic human senses evoke electrodermal activity. Sensors 23:8181
44. "Electrocardiogram (EKG/ECG)," Cleveland Clinic. [Online]. Available: https://my.clevelandclinic.org/health/diagnostics/16953-electrocardiogram-ekg. Accessed 07 Aug 2024
45. Sarvazyan AP, Tsyuryupa SN, Calhoun M, Utter A (2016) Acoustical method of whole-body hydration status monitoring. Acoust Phys 62:514–522
46. Mengistu Y, Pham M, Do HM, Sheng W (2016) AutoHydrate: a wearable hydration monitoring system. In: 2016 IEEE/RSJ international conference on intelligent robots and systems (IROS), pp 1857–1862. https://doi.org/10.1109/IROS.2016.7759295
47. Quarti-Trevano F, Seravalle G, Dell'Oro R, Mancia G, Grassi G (2021) Autonomic cardiovascular alterations in chronic kidney

disease: effects of dialysis, kidney transplantation, and renal denervation. Curr Hypertens Rep 23:10
48. de Moraes J et al (2018) Advances in photopletysmography signal analysis for biomedical applications. Sensors. https://doi.org/10.3390/s18061894
49. Feng Y, Fang G, Qu C, Cui S, Geng X, Gao D, Qin F, Zhao J (2022) Validation of urine colour L*a*b* for assessing hydration amongst athletes. Front Nutr. https://doi.org/10.3389/fnut.2022.997189
50. Belasco R, Edwards T, Munoz AJ, Rayo V, Buono MJ (2020) The effect of hydration on urine color objectively evaluated in CIE L*a*b* color space. Front Nutr 7:576974
51. "The science of nutrition and healthy eating: Week 3: 2 | OpenLearn - Open University." Accessed: Aug. 27, 2024. [Online]. Available: https://www.open.edu/openlearn/mod/oucontent/view.php?id=72178&section=2. Accessed 25 Aug 2024
52. Calhoun MC, Utter A, McAnulty SR, McBride JM, Zwetsloot J, Austin M, Mehlhorn JD, Sommerfield L, Tsyuryupa S, Sarvazyan A (2015) Validity of an acoustic method to assess whole-body hydration status. Proc Meet Acoust 23:020001
53. Kreinin A (2017) Study details | analysis of sweat secretion and body dehydration monitoring | ClinicalTrials.gov. https://clinicaltrials.gov/study/NCT03229109?cond=NCT03229109&rank=1. Accessed 7 Sep 2024
54. Marks J, E. Conroy D, M. Streeper N (2023) CLINICAL TRIALS SipIT behavioral intervention clinical trial to increase fluid intake for kidney stone prevention - American Urological Association. https://auanews.net/issues/articles/2023/october-extra-2023/clinical-trials-sipit-behavioral-intervention-clinical-trial-to-increase-fluid-intake-for-kidney-stone-prevention. Accessed 7 Sep 2024