electronics

Systematic Review

Towards Data-Driven Hydration Monitoring: Insights from Wearable Sensors and Advanced Machine Learning Techniques

Apparaju Sreeharsha , Sarah McHale , Nonso Nnamoko * and Ella Pereira

Department of Computer Science, Edge Hill University, Ormskirk L39 4QP, UK
* Correspondence: nnamokon@edgehill.ac.uk; Tel.: +44-0169-565-7640

Abstract: Advancements in wearable sensors and digital technologies/computational tools (e.g., machine learning (ML), general data analytics, mobile and desktop applications) have been explored in existing studies. However, challenges related to sensor efficacy and the application of digital technology/computational approaches for hydration assessment remain under-explored. Key knowledge gaps include applicable devices and sensors for measuring hydration and/or dehydration, the performance of approaches (e.g., ML algorithms) on sensor-based hydration monitoring; the potential of multi-sensor fusion to enhance measurement accuracy and the limitations posed by experimental datasets. This review aims to address the gaps by examining existing research to provide recommendations for future improvements. A systematic review was conducted following PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. Comprehensive searches across PubMed, Scopus, IEEE Xplore and MDPI databases for academic studies published between 2009 and 2024 were performed using predefined inclusion and exclusion criteria. Two reviewers independently screened and assessed studies, with disagreements resolved by a third reviewer. Data was synthesised narratively or through meta-analysis, where applicable. The database search yielded 1029 articles, with 999 unique studies remaining after duplicate removal. After title and abstract screening, 910 irrelevant studies were excluded. Full-text evaluation of 89 articles led to the inclusion of 20 studies for in-depth analysis. Findings highlight significant progress in hydration monitoring through multi-sensor fusion and advanced ML techniques, which improve accuracy and utility. However, challenges persist, including model complexity, sensor variability under different conditions, and a lack of diverse and representative datasets. This review underscores the need for further research to overcome these challenges and support the development of robust, data-driven hydration monitoring solutions.

Keywords: dehydration monitoring; wearable devices; sensor dataset; machine learning; prisma; hydration monitoring

Citation: Sreeharsha, A.; McHale, S.; Nnamoko, N.; Pereira, E. Towards Data-Driven Hydration Monitoring: Insights from Wearable Sensors and Advanced Machine Learning Techniques. *Electronics* **2024**, *13*, 4960. https://doi.org/10.3390/electronics13244960

Academic Editor: Luca Mesin

Received: 21 November 2024
Revised: 12 December 2024
Accepted: 14 December 2024
Published: 17 December 2024

1. Introduction

Dehydration, even at mild levels, has been shown to impair concentration, reduce endurance, and increase the risk of various health complications [1]. Hydration refers to the process of maintaining an adequate balance of fluids in the body, which is essential for normal cellular and physiological functions. Conversely, dehydration occurs when the body loses more fluids than it takes in, resulting in an imbalance that can negatively impact critical bodily processes.

It may seem an elementary problem that a human may not drink enough liquid, but if this is not adequately identified and managed, it can lead to severe issues [2]. Dehydration can stem from insufficient fluid intake or result from external factors such as excessive sweating, heat exposure, or intense physical activity. Additionally, numerous diseases and conditions, such as burns, diarrhea, vomiting, and bleeding, can cause significant fluid loss, leading to volume depletion [3]. Severe dehydration is particularly concerning, as its consequences can include brain damage, seizures, and even death [4].

In England and Wales, for example, there were 47 deaths in hospitals and care homes in 2015 where dehydration was the underlying cause [5]. Furthermore, the hospitalisation of elderly individuals with dehydration remains a serious and costly medical issue [6]. While dehydration is often perceived as an issue predominantly affecting the elderly or those with medical conditions, it is, in fact, a widespread condition across all demographics. In the United States alone, 75% of adults are estimated to suffer from chronic dehydration [7]. This makes hydration management a crucial component of health and well-being, influencing physical performance, cognitive function, and overall physiological stability. These impacts highlight the pressing need for precise and accessible hydration monitoring systems that can prevent dehydration before it leads to more severe consequences.

Dehydration is typically measured through invasive methods involving body fluid analysis [8] including dilution techniques, such as deuterium oxide and inulin injection, which are considered gold standards. However, these are invasive and measured in a laboratory setting [9]. Some invasive and highly accurate methods with digital tracking capability exist including the CorTemp (www.aesolutions.com.au/cortemp accessed on 2 December 2024) and e-Celsius (www.bodycap-medical.com/ accessed on 2 December 2024) which are ingestible pills that continuously monitors core body temperature, enabling guaranteed continuous recording in any environment without restricting movement. The relevance of core temperature to hydration assessment lies in its ability to provide indirect yet valuable indicators of hydration status. Core body temperature can fluctuate with hydration levels, as dehydration impairs the body's thermoregulation capacity (i.e., ability to control its internal temperature), leading to increased body water loss during physical activity or heat exposure [10,11]. Unfortunately, the single use CorTemp sensors that passes through the body comes at a cost (approximately $70 each), thus financially unsustainable for continuous monitoring.

Bioelectrical impedance analysis (BIA) is a non-invasive alternative that can be conducted remotely from the subject. BIA directly correlates with total body water, as it measures the opposition to electrical current flow, which is influenced by water content [12]. When the body is well-hydrated, there is more water to conduct the current, resulting in lower impedance, whereas dehydration reduces body water, increasing impedance. Some consumer-grade devices such as Withings Body+ scale (www.withings.com/eu/en/scales accessed on 2 December 2024) and Samsung Galaxy Watch (https://www.samsung.com/uk/watches accessed on 2 December 2024) now offer BIA.

Unfortunately, BIA is not recommended for clinical dehydration because its accuracy is influenced by factors like body composition, temperature, skin characteristics and physical activity levels [13]. Each of these factors require a dedicated sensor to measure them and there is no existing wearable device that can capture all of them. Moreover, there is a need to model data from the various sensors into a meaningful measure for dehydration. As such, Sawka et al. [14] concludes that traditional methods for assessing hydration, while effective, present significant challenges for continuous monitoring due to their invasive nature and/or logistical demands.

In response, recent developments in sensor technology have enabled continuous, non-disruptive hydration tracking through wearable devices. Among commercially available devices, Empatica E4 (www.empatica.com/research/e4/ accessed on 2 December 2024) and Shimmer3 GSR (https://shimmersensing.com/product/shimmer3-imu-unit/ accessed on 2 December 2024), have become prominent in both research and applied contexts. These devices incorporate an array of sensors, designed to capture physiological markers associated with hydration. The devices employ various technologies, including BIA, photoplethysmography (PPG), galvanic skin response (GSR), and sweat analysis, increasingly integrating these methods into compact wearable formats that offer the potential for real-time hydration assessment [15,16]. Despite their promise, challenges remain in translating raw sensor data into reliable hydration metrics. Environmental factors, physical activity levels, and individual physiological variability introduce complexities that hinder consistent hydration assessment across contexts.

Computational techniques like Machine learning (ML) algorithms hold relevance in this domain where accurate hydration status is essential to optimise performance and mitigate health risks.

Indeed, ML algorithms have been shown to enhance existing technologies for hydration monitoring by processing data streams from multiple sensors, increasing measurement accuracy, and enabling individualised hydration assessments [16–19]. Additionally, approaches based on software applications [20,21] and general data analytics [22,23] have been proposed. Despite substantial advancements in sensors and digital technologies for real-time, non-invasive hydration assessment, challenges still remain [24].

These challenges are not unique to hydration monitoring, as similar issues have been observed in other fields that utilise sensor-based technologies, particularly in physical activity monitoring [25], which is one of the pioneering areas of sensor-based human monitoring. Nonetheless, this review specifically concentrates on studies relevant to hydration monitoring.

Existing review articles on hydration research offer valuable insights, while also highlighting areas that could benefit from further exploration. For example, Tahar et al. [26] examines various sensors for hydration monitoring, but there is limited discussion on the integration of ML models. Similarly, Alexandre et al. [27] addresses key challenges in hydration assessment, with less emphasis on the potential contributions of ML. Reviews like Li et al. [28] focused on specific populations, and the role of data-driven approaches, including ML, but failed to address dataset paucity which is a key concerns observed in studies that applied ML algorithms for hydration and/or dehydration monitoring. Specifically, the availability (or lack) of public datasets for hydration research has not been sufficiently discussed, which limits the application of ML models in real-world scenarios. To address these challenges, researchers are increasingly utilising sensor fusion—the process of combining data from multiple sensors to create a single data point that is more robust and confident than any one sensor alone [17,29]. The goal is to extract more useful information than can be obtained from a single sensor but there is a lack of coverage in existing literature about their performance with ML approaches. Although Chiao et al. [30] examined biosignal monitoring trends, the review lacked a focused discussion on the role of multi-sensor systems and their potential for enhancing hydration monitoring accuracy. The review also overlooked broader datasets and environmental diversity, which are essential for general applicability and validation. Addressing these limitations—sensor variability, the role of multi—sensor fusion, and dataset shortcomings—–forms the core motivation for this review.

This paper presents a systematic literature review of recent advancements and persistent challenges in hydration management studies that explored the use of sensors for monitoring hydration, leveraging digital technologies such as software applications (mobile or desktop), data analytics, and machine learning. We assess the efficacy of various sensor types alongside a range of approaches to hydration assessment. The role of multi-sensor fusion in enhancing measurement accuracy is examined, as well as the practical limitations encountered in real-world applications. By synthesising existing methodologies, this review seeks to provide insights into the current state of wearable hydration monitoring technologies and identify key directions for future research and development, with a focus on improving reliability, adaptability, and applicability across diverse populations.

The rest of the paper is structured as follows: Section 2 provides details about the design approach for this review including search terms, inclusion and exclusion criteria; as well as the methods used to validate the search and review protocols. Section 3 presents a comprehensive report of related (included) work and the necessary background for the methods, tools and datasets used for experiment in the reviewed studies. This includes details of the experimental datasets found in the literature related to the subject. Key findings and results analysis, including potential threats to validity are discussed in Section 4. Section 5 summarises the study and points out future work.

2. Methods

This systematic review was conducted following the guidelines outlined in the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) [31] statement. This approach was chosen over other review approaches to address the lack of comprehensiveness found in other reviews in this area, particularly those examining persistent challenges such as sensor variability, the role of multi-sensor fusion, and limitations in experimental datasets. Alternative review designs, such as scoping or narrative reviews, were considered but found less suitable for the objectives of this study. Scoping reviews, while useful for mapping the extent of research in emerging fields, lack the depth needed to critically assess methodological quality and derive insights into key challenges. Narrative reviews, although beneficial for providing a general overview, are often less systematic and may introduce selection bias, making them unsuitable for exploring nuanced issues like model complexity and dataset diversity. Given the limited number of existing reviews that adequately address the persistent challenges in the area, a systematic review approach was deemed most appropriate. Its structured methodology allowed for a focused evaluation of studies leveraging digital technologies such as software applications (mobile or desktop), data analytics, and machine learning, for sensor-based hydration/dehydration monitoring. Specifically, the use of PRISMA ensures the inclusion of high-quality studies, thus providing a good foundation for identifying gaps.

A comprehensive search strategy was developed and applied across multiple electronic databases, including PubMed, Scopus, IEEE Xplore and MDPI, to identify relevant academic studies published between 2009 and 2024. Justification for this period stems from the popularity and growing use of ML and advanced computational techniques for hydration assessment in recent years. This growth is largely due to the promotion of electronic health records (EHRs) by the U.S. government in 2009 [32], which marked the beginning of the availability of large medical related datasets. Therefore, this review focuses on papers published from 2009 onwards.

Search terms were designed to capture variations in terminology related to applications of digital technologies/computational tools in hydration and/or dehydration and the search strings used in the study is presented in Appendix A. Detailed information about the search strategy is also presented in Section 2.1. Studies were included if they met predefined eligibility criteria discussed in Section 2.2. Titles, abstracts, and full texts were screened independently by two reviewers to ensure consistency and minimise bias. Disagreements were resolved through discussion or consultation with a third reviewer (see Section 2.4). Data extraction was performed using a standardised form, capturing key variables such as study aim, method(s), dataset(s) including availability and device used for collection, sample size, outcomes and any further remarks (see Table 1).

The quality of included studies was assessed using a specialised screening tool called MultiMetaFilterCSV (also used in Lopes et al. [33]), and a narrative synthesis or meta-analysis was conducted where appropriate.

2.1. Search Strategy, Terms and Strings

To find relevant research work, we used a two-pronged approach to search and select relevant articles. Primary databases such as Elsevier Scopus and IEEE Xplore were searched automatically using predefined search strings due to their advanced search feature that supports nested Boolean queries. Scopus was pivotal because it aggregates content from other specialised databases, including IEEE Xplore, MDPI, and PubMed, ensuring broad multidisciplinary coverage. For example, Scopus indexes computing and engineering-focused content from IEEE, journals from MDPI such as Sensors and Mathematics, and medical studies from PubMed. This was complemented with further automated search in IEEE Xplore to ensure that no significant studies in computing and engineering were missed.

The keywords used to search for articles in this systematic review were developed based on initial literature searches and refinement in Scopus and IEEE Xplore. We started with broad terms derived from the review objectives, such as 'wearable devices', 'non-invasive', and 'hydration monitoring', to form the basis of the search terms. These were iteratively refined by reviewing relevant articles and their indexing terms, incorporating additional relevant keywords identified in the process. English synonyms and domain-specific terms were incorporated to broaden the search scope. For example, to incorporate 'artificial intelligence' research, common terms like 'machine learning' and 'deep learning' that are typically used to describe the concept were included. Boolean operators (AND & OR) were systematically applied to combine terms, and pilot searches in Scopus and IEEE Xplore helped optimise search strings based on the relevance of retrieved results and further keywords identified from them e.g., related concepts like 'classification' and the names of specific algorithms. The final search strategy, including the exact terms and combinations used, was documented to ensure transparency and reproducibility.

The exact search strings and filters applied are provided in the Appendix A for transparency. Two search strings, one general Appendix A.1 and the other focused on digital technologies Appendix A.2, were applied to extract relevant papers from these databases. The general search string was designed to cover a broad range of topics related to human hydration and the use of sensor technologies for monitoring hydration states. It includes keywords and phrases such as 'human subjects', 'hydration monitoring', 'bioelectrical impedance analysis', and 'wearable biosensors', ensuring a focus on technologies that can assess hydration levels in real-time. The search also emphasises monitoring and management systems, with terms such as 'continuous hydration monitoring' and 'adaptive systems,' ensuring that research on automated and long-term hydration assessment methods could be thoroughly explored. This string aimed to identify relevant studies on both traditional and emerging sensor technologies used in hydration monitoring for human health applications. The overarching objective was to identify available datasets used in sensor-based studies that may or may not have applied digital technology/computational tools as part of their experiments. This is particularly useful to address the persistent issue of dataset limitations for experiments found in existing reviews.

The digital technology/computational tool search string was tailored to capture research utilising advanced data science methodologies and ML models in hydration studies. This search included a variety of terms related to data science, such as 'data processing', 'principal component analysis', 'unsupervised learning', and 'predictive modelling', to ensure coverage of studies using statistical and computational approaches to assess hydration. Specific ML algorithms, such as 'long short-term memory (LSTM)', 'decision trees', and 'neural networks', were also included to identify research that employed these techniques. The search also captured broader themes such as 'performance metrics' and 'model optimisation' to explore the effectiveness and accuracy of ML models in hydration-related research. This string is aimed to ensure a wide-reaching and thorough review of the intersection between hydration monitoring and ML techniques. This is important to provide insight into existing methods for sensor-based hydration monitoring, thus, addressing the lack of comprehensive information (in existing reviews) about persistent challenges such as sensor variability, and the role of multi-sensor fusion.

Manual searching was also deemed necessary in two secondary databases (MDPI and PubMed) to identify relevant articles that might not have been captured by automated search strings due to differences in indexing practices, keyword use, or metadata completeness. While MDPI supports basic Boolean operators (e.g., AND, OR, NOT) and phrase searches using quotation marks, it lacks more advanced features such as nested Boolean queries. Thus, to retrieve highly relevant studies, MDPI required a more manual and iterative approach, relying on keyword searches and post-search filtering. PubMed was also searched manually to explore its relevance beyond its primary focus as the MEDLINE database of life sciences and biomedical topics. This involved a structured and deliberate review of titles, abstracts, and keywords in hydration-related collections. We aimed to identify studies that utilised sensor datasets and applied digital solutions, including advanced data analytics, for hydration management. By combining Scopus' broad multidisciplinary indexing with database-specific searches tailored to each platform's capabilities, our strategy ensured a wide and thorough capture of relevant literature, supporting a comprehensive and inclusive systematic review.

2.2. Inclusion and Exclusion Criteria

The inclusion criteria prioritise experimental, observational, and empirical studies published in peer-reviewed academic journals involving human subjects at risk of dehydration. These subjects range from athletes and the elderly to patients with adipsia and soldiers, though this is not an exhaustive list of at-risk groups. To encompass a broad spectrum of individuals, the term 'human' was used in the search string, with the inclusion and exclusion criteria determining the final selection of studies.

Key interventions leveraging non-invasive sensors and digital technologies/computational tools for hydration monitoring. For examples, non-invasive sensors commonly used for hydration monitoring includes bioimpedance, GSR, PPG, and other wearable biosensors either as standalone or integrated into a device. The digital technologies/computational tools include software applications (mobile or desktop), data analytics, and ML models (e.g., LSTM, support vector machine (SVM), decision trees, convolutional neural network (CNN), generative adversarial network (GAN), random forests). A thorough search was conducted for publicly available datasets that utilise these sensors, specifically focusing on studies that apply them to hydration and dehydration purposes, such as hydration status prediction and fluid balance monitoring. This includes studies that compared approaches e.g., ML models versus other hydration techniques or personalised versus generic hydration models. Outcomes of interest include the accuracy of monitoring methods, efficacy of sensors, ML performance metrics (e.g., accuracy, sensitivity), and real-time biofeedback effectiveness.

Studies involving non-human subjects and those that relied solely on invasive methods, such as blood tests, were excluded to ensure the relevance of the review to human-centric, non-invasive hydration monitoring approaches, which are more suitable for everyday use outside of clinical settings. Research that did not incorporate non-invasive sensors, data science, or wearable technologies was excluded to focus on solutions that are user-friendly, practical, and designed for personal use, rather than requiring a healthcare professional or clinical environment. Additionally, studies addressing niche health conditions unrelated to general hydration were excluded to ensure the findings are broadly applicable to the general population. Papers lacking measurable outcomes or empirical data were excluded as they do not provide the objective, evidence-based insights necessary for meaningful analysis. Finally, non-English language papers were excluded unless a translation was available, to maintain consistency and accuracy in the interpretation of results.

2.3. Search Outcome

An initial search across the Elsevier Scopus and IEEE Xplore databases yielded a total of 1029 articles. After removing duplicates, 999 unique articles remained, with 30 articles identified as duplicates. A preliminary title and abstract screening were then conducted on these 999 unique articles using the MultiMetaFilterCSV specialised tool [34], which led to the exclusion of 910 articles deemed irrelevant to the study's focus. This process resulted in 89 articles being selected for full-text retrieval.

During the full-text retrieval phase, 32 articles were further excluded due to incomplete content, leaving 57 articles for in-depth screening based on the inclusion and exclusion criteria. Upon applying these criteria, 20 articles were ultimately included in the study, while 37 articles were excluded. The selection process outlined in Figure 1 follows the template from the PRISMA 2020 guidelines [31], illustrating the systematic flow from initial search to final inclusion.

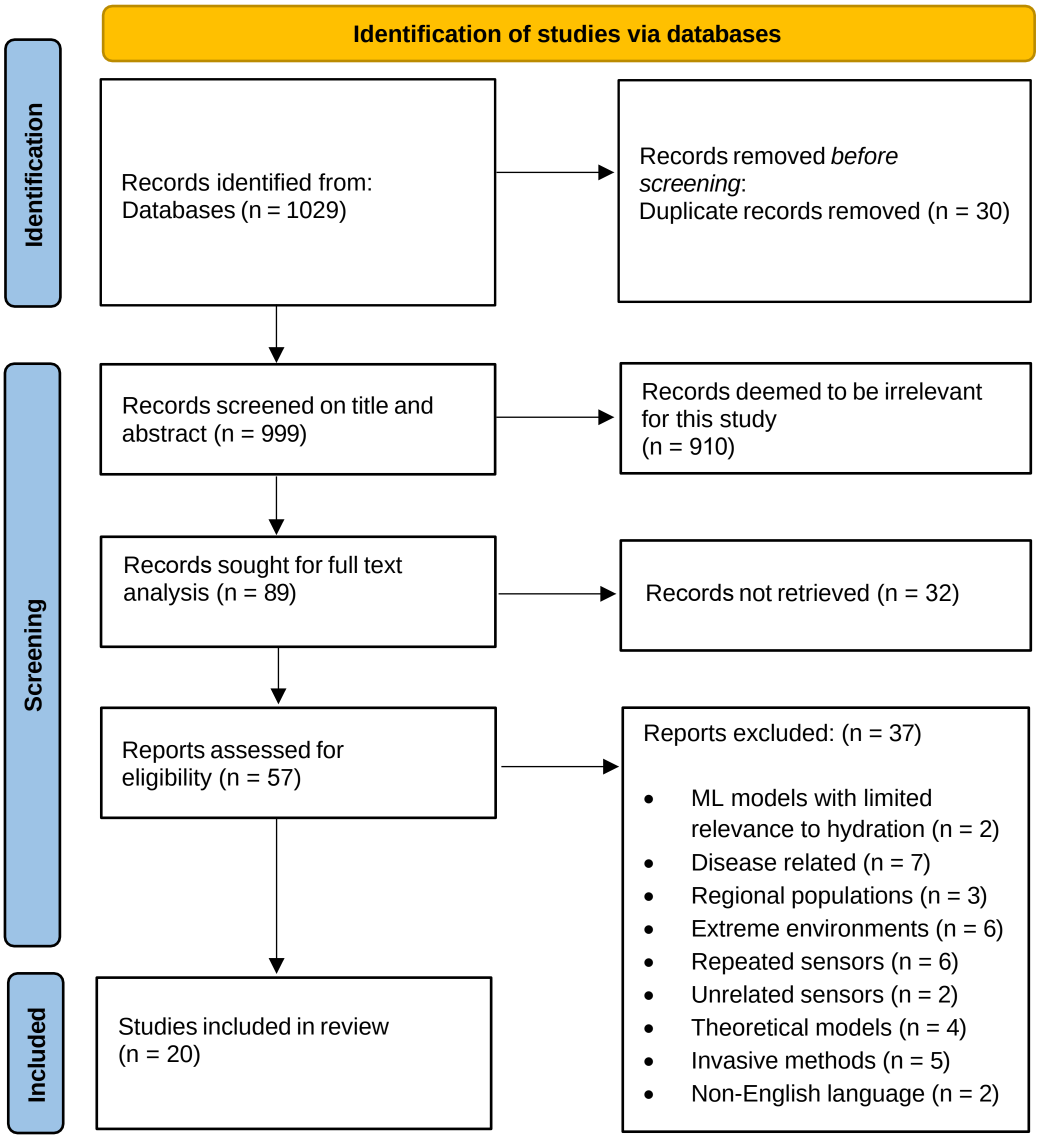

Figure 1. PRISMA diagram showing the flow of review process.

2.4. Quality Appraisal

A rigorous and multi-step screening process was implemented to ensure the inclusion of relevant and high-quality studies. Initially, structured search strings were applied across two major academic databases: IEEE Xplore and Elsevier Scopus. The metadata from the search results was exported to a local drive in CSV format. These CSV files were then processed using a specialised screening tool developed by Lopes [34]. This tool facilitated an efficient screening process by allowing for the examination of titles and abstracts to identify relevant studies and exclude irrelevant ones based on predefined inclusion and exclusion criteria. Additionally, the tool was able to detect and remove duplicate entries, further refining the dataset. Following the initial screening, all selected studies underwent a full-text analysis. This phase involved an independent review by two reviewers (authors AS and SM) to ensure objectivity and reduce bias. In cases where disagreements arose regarding the inclusion or exclusion of studies, a third reviewer (author NN) was consulted to provide an impartial perspective. The resolution of discrepancies followed a structured process: initially, AS and SM engaged in detailed discussions to clarify the criteria and rationale for their decisions. For example, when assessing whether a particular paper met the inclusion criteria, AS and SM presented their perspectives on specific aspects of the paper, such as its relevance to the topic and adherence to methodological standards, which were critically evaluated until an agreement was reached. If consensus was still not achieved, NN independently evaluated the studies in question and facilitated a final decision. This multi-step approach ensured that all decisions were made collaboratively and transparently. By incorporating these consensus discussions, the reliability and validity of the study selection process were significantly enhanced, in line with PRISMA guidelines, thereby strengthening the overall rigor of the methodology. The 20 included articles are summarised in Section 3.

Table 1. Summary of studies included in the systematic review.

Authors	Study Aim	Datasets, Devices and ML Methods	Results & Conclusions	Limitations & Future Work
Tonello et al. [20] ‡	IoT based system with Inkjet printer multi sensing wearable bracelet that is non-invasive and require no active user involvement.	**Method(s)**: Custom software device development. **Core sensors**: Tetra-polar Segmental BIA, Serpentine pattern resistance temperature detector (RTD), interdigitated electrode (IE) local hydration sensors. **Dataset(s)**: Not available. **ML model**: Not applicable.	The sensor system (BIA, IE, RTD) accurately monitored hydration and temperature. The RTD sensor had excellent linearity, and the read-out circuit worked well with slight sensitivity loss at high hydration. Low Power Wide Area Network (LoRaWAN) reliably transmitted data every 10 s, making the system effective for real-time hydration monitoring.	Future work on a full prototype for data collection, enabling development of a ML module to label hydration levels during in vivo tests. The system shows promise but addressing sensitivity at higher hydration levels and refining the prototype will further enhance its performance.
Sabry et al. [17]	The study used a Shimmer3 GSR unit to collect data from 11 subjects, applying non-linear ML algorithms for predicting hydration levels as a regression problem.	**Method(s)**: Classification tasks. **Core sensors**: (Shimmer3 GSR)—Accelerometer, magnetometer, gyroscope, GSR, PPG, temperature, and barometric pressure sensor. **Dataset(s)**: Publicly available. **ML models**: Regression (Linear, Losso, Ridge), ElasticNet, SVM, Linear ANN, Extra Trees, Random Forest, deep neural networks (DNNs).	Non-linear models, particularly random forest, and DNNs outperformed linear models in predicting hydration levels. Random forest achieved the lowest training time and comparable accuracy, making it suitable for wearable devices, while DNN excelled in model size.	Optimise model size with TinyTL and benchmark power consumption, latency, and accuracy on TinyML hardware. Current results require validation to ensure reliability.
Kulkarni et al. [29]	A novel, real-time Android tool was proposed to detect dehydration levels using wearable electrodermal activity (EDA) sensors (also known as GSR), combined with signal processing and ML, providing alerts through an application.	**Method(s)**: Classification tasks plus mobile application development. **Core sensors**: (Empatica E4)—Accelerometer, PPG, EDA, and temperature sensor. **Dataset(s)**: Not available. **ML models**: Random Forest, Decision Tree, Naíve Bayes, BayesNet, and Multi-layer Perceptron.	EDA is effective for detecting hydration levels non-invasively using the Empatica E4 device. Decision tree outperformed other algorithms, achieving 81% accuracy with raw data, 85% accuracy with 12 features after deconvolution-based feature extraction, and 93% accuracy with 14 features.	Future work aims to improve deconvolution-based feature extraction methods and validating the model on a larger user base. Further validation would be beneficial to enhance the reliability and generalisability of the results across diverse populations.
Severeyn et al. [22] ‡	Evaluate heart rate variability (HRV) in athletes during a dehydration protocol to detect declines in athletic performance, fatigue at submaximal intensities, and cardiovascular changes. This is achieved by analysing electrocardiographic signals across three stages: Rest, post-exercise, and post-hydration.	**Method(s)**: Data analytics. **Core sensors**: Electrocardiographic (ECG) signals from Cardiosoft ENCARDIA module. **Dataset(s)**: Not available. **ML models**: Not applicable.	Parameters from heart rate variability (HRV), can effectively differentiate between hydration and dehydration phases in athletes. This enables early detection of dehydration using readily available and non-invasive ECG signals.	Expanding the database, applying the protocol to diverse populations, testing with more intense exercise, and assessing HRV in hydrated subjects. Although the current system provides valuable insights, there are considerations regarding its size and cost that may affect its accessibility for personalised healthcare.

Table 1. *Cont.*

Authors	Study Aim	Datasets, Devices and ML Methods	Results & Conclusions	Limitations & Future Work
Manimegala et al. [21] ‡	A wearable sweat analyser patch detects dehydration by measuring the concentration of potassium and sodium. It features a micro storage system, counter electrode, and reference electrode, and connects to a microcontroller with Bluetooth to display data on a mobile application.	**Method(s)**: Mobile application development. **Core sensors**: (sweat patch)—counter electrode made from screen-printed Silver Chloride (AgCl) nanoparticles on Polydimethylsiloxane (PDMS). **Dataset(s)**: Not available. **ML Modes**: Not applicable.	While the results have been presented, they could benefit from more thorough discussion. The main observation is an increase in haemoglobin, haematocrit, and plasma solids suggests higher dehydration levels, yet additional context and interpretation are needed to fully understand these findings.	The current wearable devices may require further evaluation to enhance the measurement accuracy and reliability.
Yang et al. [23] ‡	To develop a cost-effective, high-performance, and flexible sweat sensor for real-time monitoring of potassium (K^+) and sodium (Na^+) concentrations in human sweat for hydration assessment.	**Method(s)**: Statistical data analysis. **Core sensors**: The sweat sensor consists of six layers: polyethylene terephthalate, Ag/AgCl, carbon, poly(3,4-ethylenedioxythiophene) polystyrene sulfonate, ion-selective membrane, and an insulating layer. **Dataset(s)**: Not available. **ML models**: Not applicable.	With more exercise days, the K^+ concentration increased while the Na^+ concentration decreased, indicating that continuous exercise may enhance the body's resistance to dehydration.	A potential limitation of the study is that the sensors' long-term effectiveness in diverse real-world conditions and across various populations remains to be fully assessed, which could influence their broader applicability.
Ring et al. [18]	To develop a two-stage ML regression approach for correcting temperature-distorted bioimpedance and estimating total body water (TBW) loss based on the corrected bioimpedance, using both linear and non-linear methods.	**Method(s)**: Regression analysis. **Core sensors**: BIA device, temperature sensors, wight measurement scale. **Dataset(s)**: publicly available [35]. **ML models**: Ordinary least squares(OLS), E-supportvector regression (ϵ-SVR) with a radial basis function (RBF) kernel.	The two-stage ML approach improved TBW loss estimation but still faced significant individual errors due to natural temperature variations and challenges like TBW underestimation with ϵ-SVR, suggesting the need to consider additional factors for improved accuracy.	The future work considers factors influencing bioimpedance, such as skin blood flow, to improve the accuracy of TBW loss predictions. Limitations include insufficient training data for baseline conditions and the ϵ-SVR's consistent underestimation of TBW loss, indicating that temperature alone may not capture all influences on bioimpedance.
Tavassolian et al. [36] ‡	A method with the potential for non-invasive and rapid hydration assessment of an individual based on nuclear magnetic resonance (NMR) relaxation measurements.	**Method(s)**: Data analytics. **Core sensors**: NRM radio frequency (RF) probe. **Dataset(s)**: Not available. **ML models**: Not applicable.	The transverse relaxation time (T2, eff) values decreased with weight loss during dehydration, indicating that specific tissue measurements can effectively reflect hydration status. Lightweight mice tolerated 72 h of dehydration, while heavier mice showed discomfort after 36 h.	Future research aims to correlate NMR measurements with existing hydration techniques and develop a portable hydration monitor. While the study validates its findings through mice samples, no human trials have been conducted, highlighting the need for further research to explore potential non-invasive applications in humans.
Songkakul et al. [37] ‡	Presents a wearable continuous hydration monitoring system consisting of custom wireless bioimpedance spectroscopy (BIS) electronics and conformable silver nanowire electrodes.	**Method(s)**: Desktop application development. **Core sensor**: BIS. **Dataset(s)**: Not available. **ML models**: Not applicable.	Circuit validation shows a mean resistance root mean square error (RMSE) of 0.971 Ω and reactance RMSE of 2.173 Ω, reflecting impedance changes due to tissue moisture loss. In vitro tests confirm increases in fluid resistance and a decrease in membrane capacitance as hydration decreases.	Optimising electrode design, integrating advanced signal processing and ML for hydration level isolation, and conducting in vivo validation against a gold standard hydration sensing device.

Table 1. *Cont.*

Authors	Study Aim	Datasets, Devices and ML Methods	Results & Conclusions	Limitations & Future Work
Alaslani et al. [38]	Involves using a smart phone for non-invasive self-monitoring of one's hydration level, which is assessed both as a binary classification (hydrated vs. dehydrated) and on a four-class scale (1 to 4). By recording a fingertip video, a PPG signal is extracted to detect hydration changes.	**Method(s)**: Classification tasks. **Core sensors**: 30 Hz camera from a Vivo android phone. **Dataset(s)**: Direct link not provided. **ML models**: K-nearest neighbors (*K*-NN), support vector machines, shallow neural networks, LSTM full connected network (LSTM-FCN), Bidirectional LSTM-FCN, DistilBERT, and 1D Vision Transformer.	The LSTM-FCN model achieved binary classification accuracies of 89.5% to 99.65%, while transformer models reached 93.08% to 99.57% for four-class classification, indicating reliance on larger datasets. A combined LSTM-FCN and t-distributed stochastic neighbor embedding method demonstrated competitive accuracies of 89.8% to 96.8% for binary and 90.2% to 94.1% for four-class classification.	Future work will refine the smartphone-based dehydration monitoring system for better accuracy across diverse populations. Limitations include the need for validation in non-fasting individuals and broader demographic groups.
Rodin et al. [16] ‡	Dehydration body monitor (DBM) sensor attached to Samsung Gear S2 and Gear Fit2 smartwatches collects sweat data via a galvanic system, processes it, and sends it to a smartphone for real-time, non-invasive hydration monitoring.	**Method(s)**: Mobile application development. **Core sensors**: PPG based DBM attached to Samsung Gear S2 and Samsung Gear Fit2 smart watches. **Dataset(s)**: Provided on Mendeley as 'SpectroPhon DBM Subject Data' [39]. **ML models**: Not applicable.	The DBM showed strong accuracy in measuring hydration levels, with Pearson correlation coefficients between 0.8885 and 0.9511, and minimal bias compared to standard weight change methods. It performed slightly better in men and was reliable across different models.	Future work aims to enhance DBM accuracy across genders, explore more wearable models, and test in varied conditions. Minor limitations include slightly reduced accuracy for women and some variability across activities, indicating areas for refinement.
Ring et al. [19]	Sweat was induced using iontophoresis electrodes and analysed with electrolyte sensors for sodium chloride concentration and osmolality. Continuous samples during exercise were statistically analysed for correlation with TBW loss, with accuracy assessed via mean absolute error.	**Method(s)**: Regression analysis. **Core sensors**: stainless steel iontophoresis electrodes for sweat induction and electrolyte sensors for measuring sodium chloride concentration in sweat. **Dataset(s)**: publicly available [35]. **ML models**: Gaussian Process Regression, utilising an affine mean function and squared exponential covariance, evaluated with leave-one-subject-out cross-validation (LOSO-CV).	Results showed that sweat chloride concentration and osmolality significantly correlated with TBW loss (chloride: $r = 0.41$, osmolality: $r = 0.43$), with estimation errors ranging from 0.12 L to 0.95 L among subjects.	The variability in TBW loss estimation and the initial overestimation followed by underestimation of TBW loss over time, suggesting the need for further refinement in the model.
Wang et al. [40]	A wearable RF device was used to analyse the correlation between changes in received signal strength indicator (RSSI) and body water loss percentage.	**Method(s)**: Regression analysis. **Core sensor**: RF sensor. **Dataset(s)**: Not available. **ML models**: Linear regression and 3rd degree polynomial regression.	The study found a strong correlation between RSSI changes and body water loss during exercise, with a third-degree polynomial model (linear regression correlation, $R^2 = 0.83$) indicating the BioMindR device's potential for real-time hydration monitoring.	Examining the effects of heart rate and body fat on RSSI, expanding studies to diverse populations, and exploring various exercise scenarios for broader validation.
Xu et al. [41]	The study presents a wearable headband smart sensor system (WS3) that monitors sodium ion concentrations in sweat to predict dehydration states. It collects data and transmits it via Bluetooth to a mobile application, which utilises a cloud-based ML model for dehydration prediction.	**Method(s)**: Classification tasks plus mobile application development. **Core sensors**: high sensitivity sweat sensor. **Dataset(s)**: Not available. **ML models**: Deep learning based Sequence-to-Sequence (Seq2Seq) LSTM with Luong attention mechanism.	The WS3 sensor monitors sodium ion concentrations in sweat, achieving 91% accuracy in dehydration prediction with a Seq2Seq LSTM model. Its real-time capabilities enhance daily healthcare.	Future work aims to test the WS3 sensor on a broader range of subjects and developing a multisensory integration system for enhanced health predictions. While the sensor effectively monitors sodium concentration, its reliance on this single metric may benefit from further exploration of additional factors influencing hydration status.

Table 1. *Cont.*

Authors	Study Aim	Datasets, Devices and ML Methods	Results & Conclusions	Limitations & Future Work
Rizwan et al. [42]	GSR data is collected using the EDA sensor of the BiTalino kit, with two electrodes placed on the hypothenar side of the palm of the non-dominant hand.	**Method(s)**: Classification tasks. **Core sensor**: EDA sensor **Dataset(s)**: Not available. **ML models**: *K*-NN, Logistic Regression, Decision Trees, SVM, Gaussian Naíve Byes, Linear Discriminant Analysis.	A 60-s window size is best for sitting and standing postures, while a 30-s window is optimal for independent scenarios. *K*-NN outperformed other algorithms, achieving accuracies of 87.78% for sitting, 83.33% for standing, and 76.82% for independent scenarios.	The paper claims to be the first to use GSR data for ML-based hydration assessment, with future work focused on multi-class problems using advanced deep learning algorithms.
Li et al. [43]	The fluid intake monitoring approach identifies drinking times using a four-stage method: data acquisition, signal pre-processing, ML classification, and post-processing. It utilises Inertial measurement Unis and an in-ear microphone for data collection, with evaluations based on event-based and sample-based methods.	**Method(s)**: Classification tasks. **Core sensors**: gyroscope and accelerometer for motion data and a condenser in-ear microphone for acoustic data. **Dataset(s)**: Not available. **ML models**: *K*-NN, SVM, Random Forest, XGBoost.	The multi-sensor fusion method outperforms single-modal signals in identifying drinking activities, with XGBoost achieving an F1-score of 83.9% for sample-based analysis and SVM achieving 95.6% for event-based analysis.	Future work focuses on enhancing fluid intake monitoring systems by further developing multimodal signal recognition techniques and improving the accuracy of drinking activity identification.
Wang et al. [44]	To predict hydration status during endurance exercise using ML models based on physiological and sweat biomarkers.	**Method(s)**: Regression analysis. **Core sensors**: Hear rate sensor, temperature sensor, sweat Na^+ sensor, Whole body sweat rate sensor (WBSRS) **Dataset(s)**: Not available. **ML models**: Linear Regression, Support Vector Regression (SVR) with an RBF kernel, and Random Forest Regression (RFR), optimised using grid search and five-fold cross-validation.	WBSR and heart rate were the best predictors of hydration status, with sweat sodium concentration providing the highest accuracy among regional markers. Nonlinear models (SVR, RFR) outperformed linear models, especially in non-drinking sessions.	Future work will include multiple subjects, varied exercise intensities, and real-time wearable. The study is limited by its single-subject design, which may affect generalisability.
Khatun et al. [45]	The aim of the study is to develop new linear regression models for estimating TBW using BIA data, providing more accurate predictions compared to existing models.	**Method(s)**: Regression analysis. **Core sensor**: BIA, no specific device or sensor was mentioned in the study, as the data was sourced from the National Health and Nutrition Examination Survey (NHANES). **Dataset(s)**: Sourced from NHANES. **ML models**: Linear regression.	The new linear regression models for estimating TBW are highly accurate, with strong correlations (0.998 for males, 0.997 for females) and low error rates, outperforming existing models.	Future work includes improving model accuracy, testing in diverse populations, and integrating the models into wearable devices. The study relies on NHANES data, which may not represent all populations or be specific to hydration estimation, and the exclusion of additional factors that could enhance model accuracy.
Liaqat et al. [46]	To detect skin hydration levels non-invasively using EDA data and ML classifiers.	**Method(s)**: Classification tasks. **Core sensors**: EDA **Dataset(s)**: Uses the data sourced from Rizwan et al. [42]. **ML models**: Logistic Regression, Random Forest, *K*-NN, Naíve Bayes, Decision Tree, Linear Discriminant Analysis, AdaBoost, and Quadratic Discriminant Analysis.	The Random Forest classifier achieved the highest accuracy (91.3%) in detecting hydration levels, outperforming other models. Feature combinations improved performance, while Naíve Bayes showed the lowest accuracy.	Future research explores deep learning techniques, such as CNNs and LSTMs, to improve hydration detection accuracy. The study's sample size and feature set were relatively limited, which may influence the scope of the findings.

Table 1. *Cont.*

Authors	Study Aim	Datasets, Devices and ML Methods	Results & Conclusions	Limitations & Future Work
Mengistu et al. [47]	To develop a wearable system that monitors hydration and body activity in real-time, using an acoustic sensor to detect drinking sounds and a smartwatch to track physical activity, providing hydration recommendations via a smartphone application.	**Method(s)**: Classification tasks plus mobile application development. **Core sensors**: Acoustic sensor (throat microphone), 3-axis accelerometer (in a smartwatch). **Dataset(s)**: Not available. **ML models**: SVM, Gradient boosting.	The AutoHydrate system achieved 91.5% accuracy in detecting drinking activity and 89.12% accuracy in classifying body activity. User feedback showed high acceptance, with 87.5% of participants believing that a wearable reminder would help with hydration.	Future work will focus on improving comfort, power optimisation, and adding dietary detection. The small sample size of 8 subjects may impact the broader applicability of the findings, and there is potential for further improvement in sensor accuracy and user comfort.

Double dagger (‡) indicates articles that did not apply ML method but included due to the use of sensor data to monitor dehydration and/or dehydration. The information presented in this table is directly taken from the cited articles. No additional experiments or validation were conducted to verify the results.

3. Results

This section provides a comprehensive synthesis of the findings from the reviewed studies, focusing on key aspects of dehydration and/or hydration monitoring using sensor technologies and ML algorithms. A detailed analysis is provided on the characteristics, scope, and limitations of the studies in Table 1. Publicly available datasets found in these studies are also presented in Table 2, with a particular focus on their potential adaptability for advancing research. Gaps in dataset diversity and representativeness are highlighted in Section 3.2, emphasising the need for high-quality, well-curated datasets to support the development of robust solutions.

Table 2. Publicly available datasets for hydration monitoring.

Dataset Information	Size	Device(s) Used	Observations
Shimmer-raw-dataset-dehydration [17]	11 subjects	Shimmer3 GSR	11 healthy subjects (9 females, 2 males). Mean age, height, and weight, provided but individual data was not.
SpectroPhon DBM Subject Data [39]	200 subjects	Samsung watch Fit2 and S2 with SpectroPhon	Published version of dataset contains 200 samples (100 females, 100 males) out of 240 volunteers recruited. Personalisation is possible.
Quantitative Dehydration Estimation [35]	10 subjects	InBody 720 and Kern DE 150K2D for weigh	All male subjects. Personalisation is possible.

The evaluation also covers the performance and applicability of various sensor technologies, including bioimpedance, PPG, GSR, and sweat sensors (see Section 3.3). Their strengths and limitations in capturing hydration-related physiological data are explored, alongside the challenges of ensuring accuracy and reliability under varying conditions. The integration of multi-sensor fusion approaches is also discussed, demonstrating their potential to improve measurement precision.

The role of computational techniques like ML models in hydration monitoring is critically analysed in Section 3.1, focusing on their reported performance, practical applications, and challenges such as model complexity, interpretability, and scalability. The synthesis provides insights into how these models interact with sensor data and the barriers to implementing real-time solutions. Overall, the results highlight the progress made in the field while identifying significant opportunities for addressing limitations and advancing future research.

3.1. Digital Technologies & Computational Techniques

The reviewed studies present several takeaways for advancing wearable hydration monitoring through ML, demonstrating diverse model choices and performance outcomes.

A significant insight is the trade-off between model complexity and practical feasibility. Deep learning models like DNNs and Transformer architectures, such as LSTM-FCN [38], and Seq2Seg LSTM [41] achieved high accuracy but demand large datasets and considerable computational resources, which can be restrictive for real-time, resource-limited wearable devices. For instance, a smartphone-based study on PPG data used LSTM-FCN and Transformers, achieving up to 99.57% accuracy for hydration classification, showing the potential of deep learning yet highlighting the challenge of processing power and data requirements [38]. Conversely, simpler, non-linear models, particularly Random Forest and Decision Trees [29], have demonstrated strong performance in more constrained environments but the accuracy achieved is not as high as those observed with deep learning architecture. For example, a study using EDA sensors with Decision Trees achieved 85% accuracy, benefiting from deconvolution-based feature extraction and balancing performance with efficiency [29]. Another study [42] employing Random Forest and K-NN models with GSR data showed accuracy rates of around 87%, 83%, and 76% depending on posture, making these models effective for low-power, continuous hydration monitoring.

Furthermore, multi-sensor fusion has proven advantageous for enhancing accuracy. A study using gyroscope, accelerometer, and in-ear microphone data to identify drinking activities [43] found that combining sensor data significantly improved performance compared to single-sensor methods, with XGBoost achieving an F1-score of 83.9% for sample-based analysis. Similarly, models trained on multi-modal data, such as K-NN and SVM, achieved robust results, showing that combining different sensor inputs can capture a more complete physiological picture [42]. Another study on sweat analysis for dehydration estimation used Gaussian Process Regression with LOSO-CV, achieving strong correlations between sweat chloride concentration and body water loss, although the model faced overestimation and underestimation challenges over time (Ring et al. [19]). The AutoHydrate system, utilising an acoustic sensor and accelerometer, attained 91.5% accuracy in detecting drinking activity, demonstrating effective hydration monitoring and positive user acceptance for wearable reminders [47].

A study focused on predicting hydration status during endurance exercise highlighted that combining heart rate, body temperature, and sweat Na^+ concentration through models like RFR and SVR achieved higher accuracy, outperforming linear models in non-drinking sessions, suggesting that sweat Na^+ concentration is particularly valuable in hydration prediction [44]. The non-invasive detection of hydration levels using EDA data and Random Forest achieved a notable 91.3% accuracy, highlighting its efficacy with a modest feature set [46]. Lastly, linear regression models developed for TBW measurement based on BIA data displayed very high correlation scores (0.998 for males, 0.997 for females), making them highly accurate for TBW estimation, albeit constrained by the limited feature range and sample diversity in NHANES data [45].

Collectively, these findings suggest that, while advanced models like deep learning and multi-sensor fusion are promising for achieving high accuracy, simpler non-linear models like Random Forest and Decision Trees offer an efficient alternative for resource-constrained settings. Expanding datasets and field validation across diverse populations, as well as refining model architectures, will be essential for further enhancing wearable hydration monitoring as a practical health tool. This is important given the data paucity in this area as elaborated in Section 3.2.

3.2. Available Datasets

The review revealed three publicly available datasets related to hydration monitoring. These are presented in Table 2. Further discussion about each dataset is presented in Sections 3.2.1–3.2.3.

3.2.1. Shimmer3 GSR Dataset

In a study conducted by Sabry et al. [17], signals such as accelerometer, gyroscope, magnetometer, GSR, PPG, temperature, and barometric pressure were recorded from

11 subjects using the Shimmer3 GSR unit. The data was collected under two conditions: while fasting for periods of up to 15 h without food or water during the month of Ramadan, and in non-fasting conditions where subjects had consumed water within the hour prior to recording. This dataset was used to explore dehydration monitoring using ML techniques. The problem was framed as a regression task, with non-linear models like random forest and deep neural networks (DNNs) outperforming linear models. Overall, random forest showed the best balance between accuracy and computational efficiency, making it suitable for resource-constrained devices.

However, it was observed that the dataset did not contain demographic data on subjects, such as age, weight, or sex. Including demographic data is critical for predicting dehydration levels as it provides additional context that can help identify patterns or commonalities within specific groups. For instance, factors such as age and weight influence hydration needs and how dehydration manifests physiologically [48,49]. Age affects hydration requirements [50] because older adults often have diminished thirst perception and reduced kidney function, which can impair their ability to maintain fluid balance [51,52]. Similarly, children have higher water turnover relative to body weight, making them more susceptible to dehydration during activities or illnesses [48,49]. Weight also plays a role, as body composition influences water distribution and retention. Individuals with higher muscle mass typically have a higher total body water content compared to those with higher fat mass, as muscles contain more water than fat tissues [53,54]. These factors highlight the importance of demographic data, such as age and weight, in tailoring hydration monitoring systems to the specific needs of different population groups [49]. Without this information, in a training dataset, there is a risk of creating generalised models that may not account for the variability in hydration responses across different demographic groups. This can result in models that perform well during experiments but fail to cater to specific populations, such as the elderly or individuals with varying body compositions. While Sabry et al. [17] leveraged the custom dataset to build generalised ML models, the absence of demographic information limits opportunities for personalised ML approaches that could better tailor predictions to individual needs.

3.2.2. SpectroPhon DBM Dataset

In a study conducted by Rodin et al. [16], the water loss due to perspiration was monitored using both traditional and wearable sensor methods. Changes in body mass, adjusted for water intake, were measured with a digital scale as a standard reference, while two wearable devices (Samsung Gear S2 and Gear Fit2) were integrated with the DBM system, measured perspiration volume using PPG sensors. The dataset, consisting of raw data from 200 human volunteers (120 male and 120 female), was collected during a 90-min physical activity session. This session included 60 min of exercise, broken down into 15-min intervals. The dataset titled 'SpectroPhon DBM Subject Data' was made available on Mendeley Data [39].

We note that although the study description mentioned 240 subjects being recruited, only 200 were made available in the repository. Furthermore, the first 11 subjects had two measurement intervals, while the remaining 189 subjects had measurements taken over three intervals. That said, the dataset holds significant potential for advancing research in hydration monitoring. Notably, it includes demographic information, which, while not directly labeled for ML tasks, can be leveraged to engineer additional features grounded in established hydration studies. For instance, employing well-known formulas, such as Total Body Water (TBW) calculations or weight-based hydration models, can facilitate the labeling of the data for ML applications. This approach would enhance the dataset's analytical utility, enabling more detailed insights that would be impossible with the Shimmer3 GSR dataset described in Section 3.2.1; thus opening possibilities for personalised predictive modeling in the context of hydration monitoring.

3.2.3. Quantitative Dehydration Estimation Dataset

Ring et al. [19], explored the quantitative estimation of TBW loss during physical exercise through the analysis of various physiological parameters, including sweat, bioimpedance, temperature, and salivary markers. The research aimed to evaluate whether sweat chloride concentration and sweat osmolality could be reliable predictors of dehydration. The dataset published in PhysioNet [35] includes measurements from 10 subjects, capturing variables such as subject ID, age, height, and body weight changes during a 120-minute treadmill exercise. It features bioimpedance data at 1000 kHz from multiple body segments, along with temperature readings from various body parts. Additionally, the dataset contains sweat chloride concentration and osmolality, alongside salivary markers like amylase, chloride, cortisol, and potassium. This collection of physiological data facilitated the author's analysis of correlations with TBW loss.

Although smaller than the SpectroPhon DBM dataset (described in Section 3.2.2), this dataset offers valuable opportunities for personalised ML tasks. Additional features can be derived using established algorithms from hydration studies to calculate variables such as total distance covered during exercise, total weight loss, percentage weight loss, and TBW loss for each subject. These enhancements would enrich the dataset with features commonly linked to dehydration. Furthermore, the inclusion of salivary biomarkers introduces unique data that is not routinely captured with sensor-based methods. This makes the dataset distinct within this research domain, offering the potential to uncover new insights into hydration monitoring.

3.3. Common Sensors

The review shows that a variety of sensors have been explored to monitor hydration through non-invasive wearable technologies, with most approaches often employing bioimpedance, PPG, GSR, sweat analysis, and RF sensors. Bioimpedance-based methods have shown promise in hydration monitoring, and they are often combined with other sensors to improve accuracy. For instance, a study by Tonello et al. [20] developed an IoT-based system using a multi-sensing wearable bracelet equipped with Tetra-polar Segmental BIA, RTD, and IE sensors for local hydration monitoring. The study introduced linear approximations to establish relationships between sensor readings and global water content in the body and surface skin hydration, noting that while these approximations indicate good potential, they may be insufficient for precise quantification in practical applications. The authors highlighted that future improvements involving ML algorithms could enhance accuracy for such measurements. However, the study emphasised the system's capability for early warning of dehydration using a simple ordinal scale (e.g., null, moderate, significant, and severe), which aligns with its primary goal of addressing dehydration risks in the elderly. While the focus was on hardware design, the proposed configuration demonstrates potential for reliable real-time data transmission via LoRaWAN.

Another study by Ring et al. [18] applied bioimpedance and temperature sensors, combined with OLS and ϵ-SVR, to estimate TBW loss during sports, tackling the challenge of temperature-distorted bioimpedance measurements. Additionally, BIS with silver nanowire electrodes [37] enabled continuous, wearable hydration monitoring by detecting tissue impedance changes due to moisture loss. PPG sensors also play a significant role in hydration assessment, typically integrated into wearable devices or smartphones. A smartphone-based method using fingertip PPG data allowed non-invasive self-assessment of hydration, leveraging ML models like LSTM-FCN and Vision Transformers to achieve high classification accuracy [38]. Similarly, a study conducted by Rodin et al. [16] used a DBM sensor integrated into Samsung Gear smartwatches for PPG-based measurements to track hydration with strong accuracy, showing reliable correlations with traditional weight-based hydration assessments.

The review shows that sweat sensors are frequently used to measure ion concentrations, particularly sodium and potassium, which correlate with hydration status. For example, a wearable headband sensor system monitored sodium ion concentrations, achieving a dehydration prediction accuracy of 91% using a Seq2Seq LSTM model with Luong attention [41]. Another study by Yang et al. [23] used sweat sensors with screen-printed Ag/AgCl electrodes on a PDMS substrate to monitor potassium and sodium levels in physically active settings, demonstrating cost-effective, real-time hydration monitoring. Additional sweat analysis studies used iontophoresis electrodes and electrolyte sensors to assess sweat chloride and osmolality, with moderate correlations to TBW loss, although variability in estimation accuracy suggested a need for refinement [19].

EDA/GSR sensors are another popular approach in hydration studies. A study by Rizwan et al. [42] used the BiTalino kit's EDA sensor with electrodes placed on the hypothenar side of the palm to measure hydration through GSR data, achieving up to 87.78% accuracy in static and dynamic postures by applying ML models such as *K*-NN, SVM, and Logistic Regression. Sabry et al. [17] with the Shimmer3 GSR device, which incorporates accelerometers, gyroscopes, and temperature sensors along with GSR, applied ML models like Random Forests and DNNs to predict hydration levels with notable accuracy, emphasising the potential of EDA in wearable platforms. Furthermore, an Android-based tool combined EDA data from Empatica E4 sensors with decision trees, reaching up to 93% accuracy in dehydration detection, further emphasising the efficacy of EDA for hydration monitoring [29].

4. Discussion

This systematic literature review provides an in-depth exploration of hydration management using sensors and digital technologies/computational tools, highlighting both the advances and limitations in current research. A primary focus across studies is on developing non-invasive, wearable solutions capable of real-time hydration monitoring for various populations, including athletes, military personnel, the elderly, and patients at risk of dehydration. Much of the research highlights the potential of sensor fusion combined with ML to improve monitoring accuracy. However, practical and methodological challenges persist. As Ring et al. [19] noted, variability in sensor accuracy remains a concern, particularly when applied across diverse populations. Similarly, environmental factors such as temperature and humidity can significantly affect sensor performance, as discussed by Tonello et al. [20] and Sabry et al. [17]. Addressing these issues will be crucial before these technologies can be reliably applied in real-world settings.

Considerable progress has been made in hydration monitoring using non-invasive sensors, covering methods such as BIA, GSR, PPG, sweat analysis, and RF sensors. BIA-based methods, often used in conjunction with other sensors, have shown effectiveness in estimating hydration levels, but their accuracy can be impacted by environmental conditions, such as temperature fluctuations, and individual physiological differences. Studies like those of Ring et al. [19] and Severeyn et al. [22] highlight that calibration challenges and the need for individual hydration baselines persist. These tools need adjustments to account for environmental variables and personalised hydration needs, which were further emphasised by Manimegala et al. [21] and Yang et al. [23].

PPG sensors, which are available in common consumer devices like smartphones and smartwatches, have demonstrated significant potential in self-assessment applications, achieving high accuracy when paired with advanced ML models like LSTM-FCN and Vision Transformers [38]. However, ensuring reliable accuracy in varied physical conditions remains a hurdle, as PPG sensors are prone to motion artifacts. Similarly, sweat sensors hold promise for measuring electrolyte levels (e.g., sodium, potassium), which can be indicative of hydration status [23]. Despite good accuracy in studies using ML models, individual differences in sweat production and composition mean that personalised calibration and activity-specific hydration models are essential, as noted by Xu et al. [41]. These challenges were also discussed by Rodin et al. [16], who emphasised the difficulty in maintaining real-time accuracy without compromising device portability.

An interesting observation is the use of indirect means to measure hydration. As noted by Severeyn et al. [22], HRV measured from biopotential signals such as ECG provides a non-invasive method for estimating hydration status. However, HRV is generally considered an indirect measurement of hydration, as it primarily reflects autonomic nervous system function rather than directly quantifying fluid balance [55]. In contrast, direct measurements such as bioimpedance techniques like BIA and EDA are more specific to hydration monitoring because they directly assess body water content through the electrical properties of tissues. Consequently, fewer studies have focused on using ECG or other types of biopotential signals as a primary method for hydration monitoring.

Recent advancements, however, show promise in leveraging artificial intelligence to enhance the analysis of biopotential signals. A growing body of work by Laganà et al. [56] explores how AI techniques can improve the extraction of meaningful data from biopotential signals, highlighting their potential for more accurate health assessments. Furthermore, integrating AI-driven systems with multimodal approaches that combine biopotential data with bioimpedance data could lead to more accurate, personalised, and comprehensive hydration assessments. This approach represents a significant avenue for future research, offering the potential to enhance the reliability and precision of hydration monitoring across various populations and settings.

With regards to sensor technologies commonly used for data collection, the Empatica E4 has long been recognised as a valuable tool for real-time physiological monitoring, offering GSR, PPG, and temperature sensors that are particularly useful in clinical and research environments. Despite its utility, certain studies have pointed out that the device's accuracy can be impacted by motion artifacts and varying ambient conditions [57–59]. These variations can affect the reliability of assessments such as hydration levels in dynamic or uncontrolled settings.

Similarly, the Shimmer3 GSR+ is another device commonly used in sensor based research including hydration monitoring. The device is recognised for its modular and customisable design, which allows for comprehensive physiological data collection, including GSR, PPG, and accelerometer readings. This flexibility facilitates the integration of multiple data streams, such as combining accelerometery with hydration markers like Shimmer GSR, which can improve overall measurement accuracy through sensor fusion. However, as Sabry et al. [17] and Rodin et al. [16] cautioned, factors such as environmental conditions, individual physiological differences, and variations in activity levels can significantly influence sensor performance. As such, a thorough understanding of these variables is crucial to ensure the accuracy and reliability of data collected through this device for hydration research [17].

Several limitations was also noted in the methods observed in the reviewed articles. Among the methods, ML algorithms are central to interpreting data from hydration sensors, with studies utilising models ranging from simple non-linear approaches like Decision Trees and Random Forest to more complex architectures like DNNs and Transformers. The trade-offs between model complexity, accuracy, and computational demand are apparent across studies. It is important to note that different datasets and methods can yield varying results, highlighting the need for careful consideration when selecting models. Complex models often yield higher accuracy, but they are not always feasible for wearables due to resource constraints. For instance, deep learning models like LSTM-FCN achieve near-perfect accuracy in smartphone-based settings but demand significant computational power, limiting their application in real-time, low-power wearables [38].

In contrast, simpler models like Random Forest and K-NN have proven effective in more constrained environments, making them suitable for continuous hydration monitoring in low-power devices. Studies employing GSR-based hydration assessments, for example, report accuracy rates of around 91.3% using these models under controlled conditions [46]. This balance between accuracy and efficiency suggests that simpler non-linear models may be preferable for resource-limited devices. Techniques such as model compression and lightweight architecture design, as discussed by Yang et al. [23], can reduce computational demands but require further research and larger datasets for training to ensure that the models remain accurate across varied conditions; especially given that device's accuracy can be impacted by many factors e.g., motion artifacts and varying ambient conditions in the case of Empatica E4. The challenge of ensuring real-time monitoring fidelity, especially in dynamic conditions, was noted by Rodin et al. [16], further emphasising the need for better sensor technology and standardised protocols.

That said, implementing continuous learning algorithms within devices could allow models to adapt to unique patterns of individual users over time as a way to mitigate the impact of personal or environmental distortions. This requires multiple modalities to capture more user data and studies like Xu et al. [41] have pointed to the potential of multimodal data integration to improve the comprehensiveness of hydration assessments. However, data paucity evidenced in Section 3.2 and the lack of extensive cross-population studies, as pointed out by Liaqat et al. [46] and Mengistu et al. [47], remains a critical challenge for achieving generalisability. This gap highlights the need for more data as well as scalability testing across different population groups to transition wearable hydration devices from experimental stages to real-world applications. Overall, refining sensor calibration, developing efficient ML models, improving datasets, and conducting broader studies are key to improving the accuracy, reliability, and scalability of hydration monitoring technologies.

5. Conclusions

This systematic literature review addressed the study aim of exploring recent advancements and persistent challenges in hydration management studies that used sensors for monitoring hydration. We assessed the efficacy of various sensor types alongside a range of approaches to hydration assessment. The role of multi-sensor fusion in enhancing measurement accuracy was explored, as well as the practical limitations encountered in real-world applications particularly the persistent data paucity in hydration monitoring research.

By synthesising existing studies, this review provides insights into the current state of wearable hydration monitoring technologies and identified key directions for future research and development, with a focus on improving reliability, adaptability, and applicability across diverse populations. Specifically, the findings suggest that the integration of sensor technologies and ML has significantly advanced the field of hydration monitoring, enabling non-invasive, real-time assessments that were previously unachievable. Notable strides have been made through multi-sensor fusion and sophisticated ML applications, which collectively improve the accuracy and utility of hydration monitoring systems.

Despite these strides, substantial challenges remain, including the complexity of models, the variability in sensor accuracy under different conditions, and the scarcity of diverse, representative datasets. Addressing these challenges will be critical for translating hydration monitoring technologies from experimental to reliable, widely applicable tools. Continued research in this area holds promising potential to support practical, data-driven hydration management for health and performance across diverse contexts as suggested in Section 6. Specifically, we believe that overcoming current limitations in hydration monitoring research will require focused efforts on personalised calibration, expanding datasets to better capture population diversity, and developing resource-efficient ML models optimised for wearable devices.

We acknowledge that this systematic review has limitations that may affect its comprehensiveness. The search strategy relied heavily on terms commonly used in computer science to describe digital technologies, data analytics, and ML, which may have excluded relevant studies from other disciplines that use different terminology to describe similar concepts. Additionally, the review was limited to articles published from 2009 onward, which could disadvantage the general search string (in Appendix A) designed specifically for identifying datasets historically used in hydration monitoring. In other words, relevant datasets published prior to 2009 (if any) were not captured. Moreover, the focus on hydration and its synonyms in the search string may have overlooked sensor datasets originally developed for other applications but potentially adaptable for hydration monitoring. Addressing these limitations in future reviews could uncover additional relevant studies and datasets, and broaden the understanding of existing studies in the field.

6. Future Research Directions and Recommendations

Future research in wearable hydration monitoring should emphasise actionable strategies to address key limitations in existing methodologies. One critical priority is the expansion of dataset diversity to improve the generalisability and robustness of hydration models. Current studies are constrained by small, homogeneous datasets, which limit their applicability across varied populations. Expanding datasets to include individuals from diverse demographics, such as age, gender, ethnicity, and health conditions, is essential for developing universally applicable models that account for variability in hydration dynamics.

Equally important is the implementation of real-time validation in uncontrolled, real-world settings. Unlike controlled studies, real-world scenarios introduce dynamic variables such as fluctuating environments, varying physical activity, and inconsistent behaviour. A real-time validation protocol could involve deploying hydration monitors during daily routines (e.g., commuting, exercising) and cross-validating sensor data with gold-standard measurements like plasma osmolality or urine-specific gravity. This approach offers valuable insights into sensor and ML model performance, highlighting issues with accuracy, latency, and adaptability. Real-world testing also reveals how factors like sweat rate, motion artifacts, and environmental noise affect accuracy. Integrating accelerometers, gyroscopes, and signal processing techniques can help mitigate these challenges.

Additionally, advancing multimodal data fusion techniques remains a promising research direction. Combining data from multiple sensor modalities, such as BIA, GSR, PPG, and sweat sensors, can significantly enhance the depth and reliability of hydration assessments. Sophisticated ML techniques, including transfer learning, could enable models to generalise across diverse user groups with minimal retraining, further enhancing usability. However, achieving this requires the development of algorithms capable of processing multimodal data in real time, even under noisy and unpredictable conditions. By addressing these challenges, future research can pave the way for adaptive, real-time systems that dynamically adjust to individual hydration needs, delivering personalised and effective hydration management solutions.

Author Contributions: Formal analysis, investigation, validation, data curation, visualisation, writing—original draft preparation A.S.; conceptualisation, methodology, software, resources, review and editing, supervision, project administration S.M. and N.N.; validation, review and editing E.P., writing—final draft preparation N.N. All authors have read and agreed to the published version of the manuscript.

Funding: This research has been carried out as part of the Project ‘HydrateME: A personalised hydration management tool based on ML approach’, which received funding from Edge Hill University Research Investment Fund (Reference No. 85918876), awarded to SM and NN. Special thanks to the computer science department for providing time and resources to complete the research.

Data Availability Statement: All datasets reported in this systematic review are publicly available and have been accessed from reputable sources, as specified in the respective citations. No proprietary or restricted datasets were used in this study.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Appendix A.1

This is the general search string used initially to retrieve all articles on hydration with or without ML application.

```
( "human" OR"person" OR"people" OR"man" OR"women" OR"children" ) AND(
"hydration" OR"dehydration" OR"plasma osmolality" OR"urine specific
gravity" OR"Hypernatremia" OR"USG" OR"adipsia" OR"non-invasive hydration"
OR"non-invasive dehydration" OR"total body water" OR"fluid balance"
OR"fluid intake" OR"hypohydration" OR"hyperhydration" OR"hydration
status" OR"water intake" OR"electrolyte imbalance" OR"serum osmolality"
) AND( "bioelectrical impedance analysis" OR"electrodermal activity"
OR"photoplethysmography sensor" OR"bioimpedance analysis" OR"bioimpedance
sensors" OR"wearable biosensors" OR"bio-sensors" OR"skin conductance
response" OR"accelerometer" OR"GSR" OR"galvanic skin response" OR"tracking
devices" OR"non-invasive hydration monitoring" OR"dehydration assessment
devices" OR"hydration sensors" OR"wearable hydration monitors" OR"optical
hydration sensors" OR"electrical impedance sensors" OR"sweat analysis
devices" OR"skin moisture sensors" ) AND( "detection" OR"monitoring"
OR"remote" OR"continuous" OR"management" OR"personalisation" OR"sensors"
OR"electrolyte imbalances" OR"risks" OR"symptoms" OR"one size fits all"
OR"continuous hydration monitoring" OR"measurement" OR"hydration feedback
systems" OR"systems" OR"hydration management systems" OR"real-time
monitoring" OR"adaptive hydration systems" OR"hydration optimisation" )
```

Appendix A.2

This is the search string used specifically to retrieve all articles on hydration with ML application.

```
( "human" OR"person" OR"people" OR"man" OR"women" OR"children" ) AND
( "hydration" OR"dehydration" OR"plasma osmolality" OR"urine specific
gravity" OR"Hypernatremia" OR"USG" OR"adipsia" OR"non-invasive hydration"
OR"non-invasive dehydration" OR"total body water" OR"fluid balance"
OR"fluid intake" OR"hypohydration" OR"hyperhydration" OR"hydration status"
OR"water intake" OR"electrolyte imbalance" OR"serum osmolality" ) AND
( "long short-term memory" OR"LSTM" OR"decision trees" OR"DT" OR"support
vector machines" OR"SVM" OR"logistic regression" OR"random forests"
OR"K-Nearest Neighbors" OR"KNN" OR"XGBoost" OR"Q-Learning" OR"linear
regression" OR"naïve bayes" OR"gradient boosting machines" OR"GBM"
OR"LightGBM" OR"CatBoost" OR"artificial neural networks" OR"ANN" OR"ridge
regression" OR"Lasso regression" OR"K-Means clustering" OR"hierarchical
clustering" OR"DBSCAN" OR"Density-Based Spatial Clustering of Applications
with Noise" OR"Principal Component Analysis" OR"PCA" OR"Independent
component analysis" OR"ICA" OR"Autoencoders" OR"Gaussian Mixture
Models" OR"GMM" OR"Self-organising maps" OR"SOM" OR"Label Propagation"
OR"Co-Training" OR"Q-Networks" OR"DQN" OR"Policy Gradient Methods"
OR"Actor-Critic Methods" OR"Proximal Policy Optimisation" OR"PPO"
OR"convolutional neural networks" OR"CNN" OR"recurrent neural network"
OR"RNN" OR"generative adversarial networks" OR"GANs" OR"transformer
networks" OR"t-Distributed Stochastic Neighbor Embedding" OR"t-SNE"
OR"Linear Discriminant Analysis" OR"LDA" OR"Factor Analysis" OR"bagging"
OR"boosting" OR"stacking" OR"AdaBoost" ) AND
```

```
( "machine learning" OR"ML" OR"AutoML" OR"deep learning" OR"DL"
OR"reinforcement learning" OR"convolutional neural network" OR"CNN"
OR"neural networks" OR"artificial intelligence" OR"AI" OR"Gradient
Boost" OR"ensemble methods" OR"supervised learning" OR"unsupervised
learning" OR"hyperparameter tuning" OR"performance metric" OR"feature
extraction" OR"predictive modelling" OR"anomaly detection" OR"data
analytics" OR"data mining" OR"pattern recognition" OR"natural language
processing" OR"NLP" OR"data analysis" OR"predictive analytics"
OR"classification" OR"clustering" OR"regression" OR"dimensionality
reduction" OR"algorithmic analysis" OR"estimation" OR"biometric analysis"
OR"data preprocessing" OR"data visualisation" OR"model training" OR"model
evaluation" OR"data-driven decision-making" OR"Semi supervised learning"
OR"Dimensionality reduction" OR"ensemble" )
```

References

1. Foster, L. *Useful Hydration Monitoring Devices: Stay Hydrated with Technology*; Educate Fitness: London, UK, 2024.
2. El-Sharkawy, A.M.; Watson, P.; Neal, K.R.; Ljungqvist, O.; Maughan, R.J.; Sahota, O.; Lobo, D.N. Hydration and outcome in older patients admitted to hospital (The HOOP prospective cohort study). *Age Ageing* **2015**, *44*, 943–947. [CrossRef] [PubMed]
3. Office for National Statistics. *Data and Analysis from Census 2021: Deaths Involving Dehydration for 2011 to 2021 in England and Wales*; Technical Report; Office for National Statistics: Newport, UK, 2021.
4. Shaheen, N.A.; Alqahtani, A.A.; Assiri, H.; Alkhodair, R.; Hussein, M.A. Public knowledge of dehydration and fluid intake practices: Variation by participants' characteristics. *BMC Public Health* **2018**, *18*, 1346. [CrossRef] [PubMed]
5. Jenkins, J.; Office for National Statistics. *Understanding ONS Statistics on Patient Deaths*; Office for National Statistics: Newport, UK, 2017.
6. Warren, J.L.; Bacon, W.E.; Harris, T.; McBean, A.M.; Foley, D.J.; Phillips, C. The burden and outcomes associated with dehydration among US elderly, 1991. *Am. J. Public Health* **1994**, *84*, 1265–1269. [CrossRef] [PubMed]
7. Taylor, K.; Tripathi, A.K.; Jones, E.B. *Adult Dehydration*; StatPearls Publishing: St. Petersburg, FL, USA, 2022.
8. AlDisi, R.; Bader, Q.; Bermak, A. Hydration Assessment Using the Bio-Impedance Analysis Method. *Sensors* **2022**, *22*, 6350. [CrossRef]
9. Pfrimer, K.; Moriguti, J.C.; Lima, N.K.C.; Marchini, J.S.; Ferriolli, E. Bioelectrical impedance with different equations versus deuterium oxide dilution method for the inference of body composition in healthy older persons. *J. Nutr. Health Aging* **2012**, *16*, 124–127. [CrossRef] [PubMed]
10. Wakabayashi, H.; Wijayanto, T.; Lee, J.Y.; Hashiguchi, N.; Saat, M.; Tochihara, Y. A comparison of hydration effect on body fluid and temperature regulation between Malaysian and Japanese males exercising at mild dehydration in humid heat. *J. Physiol. Anthropol.* **2014**, *33*, 5. [CrossRef] [PubMed]
11. Périard, J.D.; Eijsvogels, T.M.H.; Daanen, H.A.M. Exercise under heat stress: Thermoregulation, hydration, performance implications, and mitigation strategies. *Physiol. Rev.* **2021**, *101*, 1873–1979. [CrossRef] [PubMed]
12. Pialoux, V.; Mischler, I.; Mounier, R.; Gachon, P.; Ritz, P.; Coudert, J.; Fellmann, N. Effect of equilibrated hydration changes on total body water estimates by bioelectrical impedance analysis. *Br. J. Nutr.* **2004**, *91*, 153–159. [CrossRef]
13. Dehghan, M.; Merchant, A.T. Is bioelectrical impedance accurate for use in large epidemiological studies? *Nutr. J.* **2008**, *7*, 26. [CrossRef] [PubMed]
14. Sawka, M.N.; Cheuvront, S.N.; Kenefick, R.W. Hypohydration and Human Performance: Impact of Environment and Physiological Mechanisms. *Sport. Med.* **2015**, *45*, 51–60. [CrossRef]
15. Seongbin, J.; Daeun, S.; Sungbong, K.; Jahyun, K. A review of wearable biosensors for sweat analysis. *Biomed. Eng. Lett.* **2021**, *11*, 117–129. [CrossRef]
16. Rodin, D.; Shapiro, Y.; Pinhasov, A.; Kreinin, A.; Kirby, M. An accurate wearable hydration sensor: Real-world evaluation of practical use. *PLoS ONE* **2022**, *17*, e0272646. [CrossRef] [PubMed]
17. Sabry, F.; Eltaras, T.; Labda, W.; Hamza, F.; Alzoubi, K.; Malluhi, Q. Towards On-Device Dehydration Monitoring Using Machine Learning from Wearable Device's Data. *Sensors* **2022**, *22*, 1887. [CrossRef] [PubMed]
18. Ring, M.; Lohmueller, C.; Rauh, M.; Eskofier, B.M. A Two-Stage Regression Using Bioimpedance and Temperature for Hydration Assessment During Sports. In Proceedings of the 2014 22nd International Conference on Pattern Recognition, Stockholm, Sweden, 24–28 August 2014; pp. 4519–4524. [CrossRef]
19. Ring, M.; Lohmueller, C.; Rauh, M.; Eskofier, B.M. On sweat analysis for quantitative estimation of dehydration during physical exercise. In Proceedings of the 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Milan, Italy, 25–29 August 2015; Volume 2015, pp. 7011–7014. [CrossRef]
20. Tonello, S.; Zacchini, A.; Galli, A.; Golparvar, A.; Meimandi, A.; Peruzzi, G.; Pozzebon, A.; Lago, N.; Cester, A.; Giorgi, G.; et al. Design and in-vitro Characterization of a Wearable Multi-Sensing System for Hydration Monitoring. *IEEE Trans. Instrum. Meas.* **2024**, *73*, 1–11. [CrossRef]

21. Manimegala, P.; Mary, X.A.; Biji, N.; Shiny, V.S. Dehydration measurement using sweat sensor patch and pulse sensor. *J. Phys. Conf. Ser.* **2021**, *1937*, 12013. [CrossRef]
22. Severeyn, E.; Velasquez, J.; Perpinan, G.; Herrera, H.; Pacheco, M.; Wong, S. Heart rate variability analysis during a dehydration protocol on athletes. In Proceedings of the 2016 XXI Symposium on Signal Processing, Images and Artificial Vision (STSIVA), Bucaramanga, Colombia, 31 August–2 September 2016; p. 1.
23. Yang, M.; Sun, N.; Lai, X.; Li, Y.; Zhao, X.; Wu, J.; Zhou, W. Screen-Printed Wearable Sweat Sensor for Cost-Effective Assessment of Human Hydration Status through Potassium and Sodium Ion Detection. *Micromachines* **2023**, *14*, 1497. [CrossRef] [PubMed]
24. Suppiah, H.T.; Ng, E.L.; Wee, J.; Taim, B.C.; Huynh, M.; Gastin, P.B.; Chia, M.; Low, C.Y.; Lee, J.K.W. Hydration Status and Fluid Replacement Strategies of High-Performance Adolescent Athletes: An Application of Machine Learning to Distinguish Hydration Characteristics. *Nutrients* **2021**, *13*, 4073. [CrossRef]
25. Nnamoko, N.; Cabrera-Diego, L.A.; Campbell, D.; Sanders, G.; Fairclough, S.J.; Korkontzelos, I. Personalised Accelerometer Cut-point Prediction for Older Adults' Movement Behaviours using a Machine Learning approach. *Comput. Methods Programs Biomed.* **2021**, *208*, 106165. [CrossRef]
26. Tahar, A.; Zrour, H.; Dupont, S.; Pozdzik, A. Non-invasive approaches to hydration assessment: A literature review. *Urolithiasis* **2024**, *52*, 132. [CrossRef] [PubMed]
27. Rebelo-Marques, A.; Coelho-Ribeiro, B.; De Sousa Lages, A.; Andrade, R.; Afonso, J.; Pereira, R.; Batista, A.S.; Teixeira, V.H.; Jácome, C. Trends and Missing Links in (De)Hydration Research: A Narrative Review. *Nutrients* **2024**, *16*, 1709. [CrossRef] [PubMed]
28. Li, S.; Xiao, X.; Zhang, X. Hydration Status in Older Adults: Current Knowledge and Future Challenges. *Nutrients* **2023**, *15*, 2609. [CrossRef] [PubMed]
29. Kulkarni, N.; Compton, C.; Luna, J.; Alam, M.A.U. A Non-Invasive Context-Aware Dehydration Alert System. In Proceedings of the 22nd International Workshop on Mobile Computing Systems and Applications, Virtual, 24–26 February 2021; pp. 157–159. [CrossRef]
30. Chiao, J.C.; Bing, S.; Chawang, K.; Crowe, B. Thirsty for a Noninvasive Wearable to Detect Dehydration: A Review. *IEEE Antennas Propag. Mag.* **2024**, *66*, 66–76. [CrossRef]
31. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* **2021**, *372*, n71. [CrossRef] [PubMed]
32. Habehh, H.; Gohel, S. Machine Learning in Healthcare. *Curr. Genom.* **2021**, *22*, 291–300. [CrossRef]
33. Lopes, R.; Trovati, M.; Pereira, E. Volumetric Techniques for Product Routing and Loading Optimisation in Industry 4.0: A Review. *Future Internet* **2024**, *16*, 39. [CrossRef]
34. Lopes, R. MultiMetaFilterCSV. 2024. Available online: https://github.com/rics23/multiMetaFilterCSV (accessed on 22 November 2024).
35. Ring, M.; Lohmueller, C.; Rauh, M.; Eskofier, B.M. Quantitative Dehydration Estimation. *PhysioNet* **2017**. [CrossRef]
36. Tavassolian, N.; Li, M.; Vassiliou, C.C.; Cima, M.J. A Novel Magnetic Relaxation-Based Platform for Hydration Monitoring. *IEEE Sens. J.* **2014**, *14*, 2851–2855. [CrossRef]
37. Songkakul, T.; Wu, S.; Ahmmed, P.; Reynolds, W.D.; Zhu, Y.; Bozkurt, A. Wearable Bioimpedance Hydration Monitoring System using Conformable AgNW Electrodes. In Proceedings of the 2021 IEEE Sensors, Sydney, Australia, 31 October–3 November 2021; pp. 1–4. [CrossRef]
38. Alaslani, R.; Perzhilla, L.; Rahman, M.M.U.; Laleg-Kirati, T.M.; Al-Naffouri, T.Y. You can monitor your hydration level using your smartphone camera. *arXiv* **2024**, arXiv:2402.07467. [CrossRef]
39. Kirby, M. SpectroPhon DBM Subject Data. *Mendeley Data* **2021**. [CrossRef]
40. Wang, J.; Zilic, Z.; Shu, Y. Evaluation of an RF wearable device for non-invasive real-time hydration monitoring. In Proceedings of the 2017 IEEE 14th International Conference on Wearable and Implantable Body Sensor Networks (BSN), Eindhoven, The Netherlands, 9–12 May 2017; pp. 91–94. [CrossRef]
41. Xu, W.; Hong, L.; Zheng, J.; Li, M.; Hua, Y.; Zhao, X. Wearable Smart Sensor System for Monitoring and Intelligent Prediction of Sodium Ions in Human Perspiration. *IEEE Internet Things J.* **2024**, *11*, 8146–8155. [CrossRef]
42. Rizwan, A.; Ali, N.A.; Zoha, A.; Ozturk, M.; Alomainy, A.; Imran, M.A.; Abbasi, Q.H. Non-Invasive Hydration Level Estimation in Human Body Using Galvanic Skin Response. *IEEE Sens. J.* **2020**, *20*, 4891–4900. [CrossRef]
43. Li, J.H.; Yu, P.W.; Wang, H.C.; Lin, C.Y.; Lin, Y.C.; Liu, C.P.; Hsieh, C.Y.; Chan, C.T. Multi-Sensor Fusion Approach to Drinking Activity Identification for Improving Fluid Intake Monitoring. *Appl. Sci.* **2024**, *14*, 4480. [CrossRef]
44. Wang, S.; Lafaye, C.; Saubade, M.; Besson, C.; Margarit-Taule, J.M.; Gremeaux, V.; Liu, S.C. Predicting Hydration Status Using Machine Learning Models From Physiological and Sweat Biomarkers During Endurance Exercise: A Single Case Study. *IEEE J. Biomed. Health Inform.* **2022**, *26*, 4725–4732. [CrossRef]
45. Khatun, F.; Rana, M.S.; Sarkar, A.K. Linear Regression Models for Total Body Water Measurement Based on Bioelectrical Impedance Analysis. In Proceedings of the 2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT), Dhaka, Bangladesh, 3–5 May 2019; pp. 1–6. [CrossRef]
46. Liaqat, S.; Dashtipour, K.; Arshad, K.; Ramzan, N. Non Invasive Skin Hydration Level Detection Using Machine Learning. *Electronics* **2020**, *9*, 1086. [CrossRef]

47. Mengistu, Y.; Pham, M.; Do, H.M.; Sheng, W. AutoHydrate: A wearable hydration monitoring system. In Proceedings of the 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Daejeon, Republic of Korea, 9–14 October 2016; pp. 1857–1862. [CrossRef]
48. Popkin, B.M.; D'Anci, K.E.; Rosenberg, I.H. Water, hydration, and health. *Nutr. Rev.* **2010**, *68*, 439–458. [CrossRef]
49. Liska, D.; Mah, E.; Brisbois, T.; Barrios, P.L.; Baker, L.B.; Spriet, L.L. Narrative Review of Hydration and Selected Health Outcomes in the General Population. *Nutrients* **2019**, *11*, 70. [CrossRef] [PubMed]
50. Silver, A.J. Aging and risks for dehydration. *Clevel. Clin. J. Med.* **1990**, *57*, 341–344. [CrossRef] [PubMed]
51. Rolls, B.J.; Phillips, P.A. Aging and Disturbances of Thirst and Fluid Balance. *Nutr. Rev.* **2009**, *48*, 137–144. [CrossRef] [PubMed]
52. Tanrıverdi, M.; Heybeli, C.; Çalım, Ö.F.; Durna, M.; Özturan, O.; Soysal, P. The relationship between oropharyngeal dysphagia and dehydration in older adults. *BMC Geriatr.* **2024**, *24*, 885. [CrossRef] [PubMed]
53. Rasgado-Flores, H.; Theobald, J.; Ruiz, J.; Bitner, J.B.; Markowitz, S.; Zlatnick, D.; Yee, P.A.; Yee, P.P.; Trais, L.; Gohar, K.; et al. Cell Volume Sensing and Regulation in Skeletal Muscle Cells. In *Cell Volume and Signaling*; Lauf, P.K., Adragna, N.C., Eds.; Springer: Boston, MA, USA, 2004; pp. 263–292. [CrossRef]
54. Lorenzo, I.; Serra-Prat, M.; Yébenes, J.C. The Role of Water Homeostasis in Muscle Function and Frailty: A Review. *Nutrients* **2019**, *11*, 1857. [CrossRef] [PubMed]
55. Vescovi, J.D.; Mandic, I.; Watson, G. Relationships between heart rate variability and indirect indicators of hydration status in elite male field hockey players. *Int. J. Sports Sci. Coach.* **2022**, *17*, 619–625. [CrossRef]
56. Laganà, F.; Pratticò, D.; Angiulli, G.; Oliva, G.; Pullano, S.A.; Versaci, M.; La Foresta, F. Development of an Integrated System of sEMG Signal Acquisition, Processing, and Analysis with AI Techniques. *Signals* **2024**, *5*, 476–493. [CrossRef]
57. Menghini, L.; Gianfranchi, E.; Cellini, N.; Patron, E.; Tagliabue, M.; Sarlo, M. Stressing the accuracy: Wrist-worn wearable sensor validation over different conditions. *Psychophysiology* **2019**, *56*, e13441. [CrossRef] [PubMed]
58. Sanchez-Comas, A.; Synnes, K.; Molina-Estren, D.; Troncoso-Palacio, A.; Comas-González, Z. Correlation Analysis of Different Measurement Places of Galvanic Skin Response in Test Groups Facing Pleasant and Unpleasant Stimuli. *Sensors* **2021**, *21*, 4210. [CrossRef] [PubMed]
59. Vila, G.; Godin, C.; Charbonnier, S.; Campagne, A. Real-Time Quality Index to Control Data Loss in Real-Life Cardiac Monitoring Applications. *Sensors* **2021**, *21*, 5357. [CrossRef] [PubMed]