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Artificial Intelligence in Water Consumption Forecasting: A Systematic Review

Su Tüketimi Tahmininde Yapay Zekâ: Sistematik İnceleme

Gülsüm AŞIKSOY[1*], Hüseyin GÖKÇEKUŞ[2]

[1] *Artificial Intelligence Engineering Department, Near East University, Nicosia, Mersin 10, Türkiye*

[2] *Faculty of Civil and Environmental Engineering, Near East University, Nicosia, Mersin 10, Türkiye*

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ABSTRACT

Predicting water consumption is crucial for the sustainable management of water resources and for solving the world's water problems. Water is the subject of numerous studies as it is essential for the survival of all living beings. Artificial intelligence, machine learning and conventional statistical methods have been used in these studies. This article provides a comprehensive overview of the research about AI applications for water consumption predictions. The study was conducted using articles published between 2019 and 2024, retrieved from academic databases such as SpringerLink, IEEE Xplore and Scopus. The analyzed literature was categorized based on water studies in relation to the algorithms used to predict water consumption. The study also investigated the advantages, disadvantages and difficulties of artificial intelligence methods used in water consumption estimation studies. The results show that the performance of Long Short-Term Memory models is better than other methods. Nevertheless, data quality and availability are limiting factors. This study examines recent advances in predicting water consumption using AI-based methods and identifies potential areas for further research in this field.

Keywords: Artificial intelligence, machine learning, water demand management, water forecasting

ÖZ

Su tüketiminin tahmin edilmesi, su kaynaklarının sürdürülebilir bir şekilde yönetilmesi ve dünya genelindeki su sorunlarının çözülmesi açısından hayati öneme sahiptir. Su, tüm canlıların yaşamı için vazgeçilmez olduğundan, uzun süredir birçok çalışmanın odağında yer almıştır. Bu çalışmalarda yapay zekâ, makine öğrenmesi ve geleneksel istatistiksel yöntemler kullanılmıştır. Bu makale, su tüketimi tahmininde yapay zekâ uygulamalarına dair mevcut araştırmaları kapsamlı bir şekilde incelemektedir. Çalışma, 2019 ile 2024 yılları arasında yayımlanmış ve SpringerLink, IEEE Xplore ve Scopus gibi akademik veri tabanlarından elde edilmiş makaleler üzerinden yürütülmüştür. İncelenen literatür, su tüketimini tahmin etmek için kullanılan algoritmalara göre sınıflandırılmıştır. Ayrıca, su tüketimi tahmin çalışmalarında kullanılan yapay zekâ yöntemlerinin avantajları, dezavantajları ve karşılaşılan zorluklar da değerlendirilmiştir. Elde edilen sonuçlar, Uzun Kısa Süreli Bellek (LSTM) modellerinin performansının diğer yöntemlere kıyasla daha iyi olduğunu ortaya koymaktadır. Bununla birlikte, veri kalitesi ve erişilebilirliği sınırlayıcı faktörler arasında yer almaktadır. Bu çalışma, yapay zekâ tabanlı yöntemlerle su tüketimi tahminine yönelik son gelişmeleri incelemekte ve bu alandaki gelecekteki araştırmalar için potansiyel yönleri vurgulamaktadır.

Anahtar Kelimeler: *Yapay zeka, makine öğrenmesi, su talebi yönetimi, su tüketimi tahmini.*

Sorumlu yazar / *Corresponding author:* gulsum.asiksoy@neu.edu.tr

INTRODUCTION

Water consumption has increased significantly with the growing world population and advancing technology (Piasecki et al., 2018). Water resources are critical elements for the economic development of a country or region. As worldwide population growth accelerates in parallel with economic globalization, water scarcity has become a significant obstacle to socio-economic development in many countries (Chen et al., 2021). Improving the efficiency of water management, creating a holistic framework that integrates the social, economic and environmental dimensions in harmony with the natural water cycle, conserving water as a strategic resource, and effectively planning and utilizing resources are crucial steps in sustainable development policies. Raising consumer awareness of water stewardship is also an essential part of this process (Kavurucu et al., 2022)

Water is a finite and critical natural resource that significantly influences economic and social development. Modeling and forecasting about the use of this scarce resource is crucial to effectively meet current and future demand (Dong et al., 2013). Accurately predicting trends in water use will enable the development of strategies that align resource management processes with sustainability goals and support immediate and long-term needs (Willmott, & Matsuura, 2005).

Predicting water use is important for managing resources, averting water-related crises, and ensuring the equitable distribution of available resources. For managers, these water use prediction models compensate for the time invested in developing strategies, planning for the future, and managing resources efficiently (Rustam et al., 2022). These models also help to assess the impact on water use patterns of climatic changes, population growth, the scale of economic activities and the expansion of urban settlements (Rustam et al., 2022; Yu et al., 2019).

To date, conventional methods for modeling water consumption patterns have used statistical analysis (Bejarano et al., 2019). Political, economic, and sociological factors have traditionally been modeled using linear trends. In many cases, the inclusion of water consumption is only sometimes linear or modular. This has created a need to use more advanced approaches (Ribeiro et al., 2021). Recently, there has been growing interest in artificial intelligence (AI) and other machine learning-based technologies as new tools to improve water consumption forecasting. Advantages of these methods lie in their ability to process large amounts of data, recognize non-linear dependencies, and respond flexibly to the demands of the changing environment (Pourmousavi et al., 2022).

This article provides a systematic review of the literature about the use of AI applications in predicting water consumption. By analyzing the performance of different algorithms, characteristics of data types, and model limitations based on literature reports from related fields, this study exposes the current state of affairs in this area and identifies where there may be gaps for further investigation. Ultimately, the study aims to present an overarching view that is useful for both academia and practice.

METHODOLOGY

The main objective of this study is to systematically evaluate the artificial intelligence methods used in predicting water consumption, discuss the challenges encountered and highlight the opportunities for future research. To ensure transparency and reliability, a rigorous methodology was applied based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher et al., 2009).

Databases and Screening Process

In this study, three academic databases were searched to find studies that used artificial intelligence methods to estimate water consumption: SpringerLink, Scopus, and IEEE Xplore.

During the search process, keywords such as "artificial intelligence", "machine learning", "deep learning", "water consumption", "water usage", "water demand forecasting", and "water demand prediction" were used to find studies and examine the role of artificial intelligence techniques in water consumption forecasting.

The search strategy was developed using a combination of keywords related to artificial intelligence and water demand forecasting. Boolean operators and wildcard characters were used to expand the search scope and capture all relevant literature. The Boolean search expression applied was as follows:

("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Water Consumption" OR "Water Usage" OR "Water Demand") AND ("Forecasting" OR "Prediction").

This approach ensured the inclusion of studies that used various terminology to describe AI-based water consumption prediction models. Keywords were searched in the title, abstract, and keyword fields to maximize retrieval of relevant studies.

Inclusion and Exclusion Criteria

Inclusion and exclusion criteria are summarized in Table 1.

The inclusion criteria for our study focused on selecting research that utilized artificial intelligence techniques for forecasting water consumption. Studies incorporating real-world and simulated water consumption data were also considered for analysis. The studies needed to be published between 2019 and 2024 and written in English, as these were key selection criteria. Studies using statistical methods other than artificial intelligence techniques for water consumption forecasting research were not included. In addition, duplicate studies, book chapters and conference abstracts and papers whose full texts could not be accessed were excluded. These criteria were applied to maintain focus and methodological rigor in the study.

Table 1. Inclusion and exclusion criteria for systematic review.
Çizelge. Sistematik derleme için dahil etme ve hariç tutma kriterleri.

Inclusion Criteria	Exclusion Criteria
Studies using artificial intelligence techniques for water consumption forecasting.	Studies using statistical methods other than AI-based prediction techniques.
Studies using real-world water consumption data as well as simulated data.	Duplicate studies or those with inaccessible full text.
Studies published between 2014 and 2024.	Studies with inaccessible full text.
Studies written in English.	Book chapters, conference abstracts.

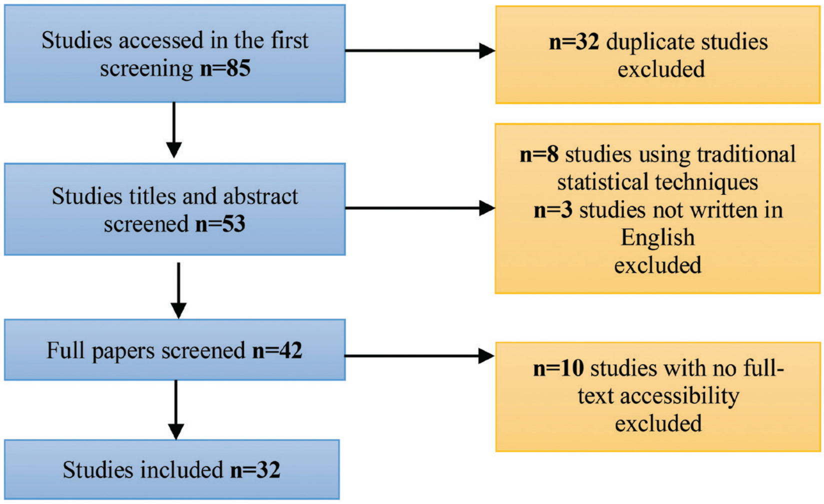

Figure 1. PRISMA flow diagram for selection process (n represents the number of studies).
Şekil 1. Çalışma seçme sürecine ait PRISMA Akış Şeması (n, çalışma sayısını temsil etmektedir).

The process for selecting relevant publications is illustrated in detail in the PRISMA flow chart in Figure 1. The initial search yielded 85 articles. After removing 32 duplicates, 53 studies remained. Of these, 8 were excluded for using traditional statistical methods and 3 for not being written in English. Another 10 studies were excluded due to lack of full-text access. Finally, 32 studies were included in the systematic analysis.

Data Reliability and Bias Assessment

For the reliability of the study, the articles were evaluated individually by two independent researchers, and then a consensus was reached on whether each study should be included. In addition, criteria such as the impact factors of the journals in which the articles were published, the number of citations of the studies, and the potential for direct application of the studies in the environmental and climatic context were analyzed in detail. Thus, it was ensured that the articles included in the systematic review were only those that met high scientific standards and were relevant to the study's objectives.

Table 2 provides a summary of the 32 studies included in this systematic review. The studies are classified according to the region in which they were conducted, the AI methods used, the dataset characteristics, the performance metrics, and the results obtained.

RESULTS

This systematic review examined 32 studies about predicting water consumption using artificial intelligence (AI) techniques. This review comprehensively analyzes the capabilities, challenges, and practical applications of AI in predicting water consumption by integrating insights from recent research, data from Excel datasets, and critical references.

Table 2. Reviewed studies about artificial intelligence based water consumption forecasting.
Çizelge 2. Yapay zekâ tabanlı su tüketimi tahminine ilişkin incelenen çalışmalar.

References	Region	AI Methods	Dataset	Performance Metrics	Results
El Hanjri et al. (2023)	Morocco	LSTM, ARIMA	Residential and institutional water usage data	RMSE	Achieved RMSE 5.60 m³ and 89% correlation, demonstrating strong predictive performance.
Cao et al. (2023)	China	LSTNet, AutoStG, ASTGCN	Hourly water consumption (1, 3, 6, 12, and 24 hours)	RMSE, MAE, RSE	ASTGCN model reached RMSE 566.4 m³, MAE 377.7 m³, and 96.4% accuracy.
Monjardin et al. (2020)	Philippines	ANN	Socioeconomic, rainfall, temperature.	R-value	ANN achieved a strong correlation of R=0.97013 between actual and predicted water usage.
(Rustam et al. 2022)	-	RF, DT, ET, LR, SVM, ADA, CNN, GRU	Kaggle and GitHub datasets for water consumption	F1, RMSE, MAE, MSE, R^2	Delivered 96% accuracy for water quality prediction.
Huang et al. (2023)	China	SAE, BPNN	Hourly water usage data	MAPE, RMSE	BPNN achieved MAPE of 2.31% and RMSE of 320 m³/hour, indicating stable short-term prediction.
Boudhaoui & Wira (2021)	France	ML, LSTM, BPNN	Hourly water consumption data	RMSE	LSTM predicted next hour consumption with minimal error, showing strong long-term dependency learning.
Farah, et al. (2019)	France	ANN	Hourly data from AMR meters	RMSE, R^2	High correlation ($R^2 = 0.902$) and accurate predictions for restaurant water consumption patterns.
Tzanes et al. (2023)	Tilos Island	Fuzzy Clustering Algorithm	Simulated water usage clusters	MAE, RMSE	Clustering reduced MAE by 29%, improving short-term water usage predictions.
Cao et al. (2024)	China	SSA-CNN-BigRU	Raw water consumption data	MAE, RMSE, R^2	Achieved 94.73% accuracy for urban water demand predictions.
Liu et al. (2023)	China	STL-ADA-LSTM	Daily water demand data for two facilities	MAE, MAPE, MSE, RMSE, R^2, AIC	Strong trend and seasonal forecasting for water facilities, but performance varied by data type.
Kim et al. (2023)	South Korea	DNN, LSTM	Daily water demand data from Gurye station	CC, NRMSE, F1	LSTM achieved 0.95 correlation and NRMSE of 8.38, demonstrating excellent performance.

Table 2. Devamı

Çizelge 2. Continued.

References	**Region**	**AI Methods**	**Dataset**	**Performance Metrics**	**Results**
Yan et al. (2022)	China	Spatial Clustering, MLP	Spatial clustering and water usage data	MAE, RMSE	Hybrid CNN-bilSTM improved deterministic and probabilistic predictions by up to 26.7%.
Wang et al. (2023)	China	ESN	Residential and agricultural water demand data	-	SN predicted water demand for 2025, with estimates varying by economic and price scenarios.
Zheng et al., (2022)	China	NARX Neural Network	Smart meter data	MAE, MAPE, RMSE	RS-NARX outperformed standard NARX models, providing better accuracy and stability.
Gutiérrez et al., (2020)	Mexico	AHN	Water flow sensor data	RMSE	Achieved a low RMSE of 2.49 liters/hour, demonstrating reliable predictions.
Oyebode (2019)	South Africa	DE with Feedforward Neural Networks	Weather, socioeconomic, and water usage data	Pearson correlation, Information gain	Feature selection techniques improved prediction accuracy over the baseline.
Ribeiro et al. (2021)	Brazil	SVR, Ridge Regression, Gaussian Proc.	Water usage data from two cities in Paraná	RMSE, MAE, MAPE	Effective multi-step forecasting using seasonal-trend decomposition and ML models.
Bejarano et al. (2019)	USA	Sparse Gaussian CRFs, LSTM, RNN	Building-level water usage data	RMSE, MAE	SwAP system improved RMSE and MAE by 50% and 44%, respectively, over baselines.
Oyebode & Ighravw (2019)	South Africa	DE, CG-SVM, ES, MLR	Real-world data from Ekurhuleni City	R^2, MAPE, RMSE	Evolutionary computing techniques effectively enhanced predictive performance for urban water demand.
García-Soto et al. (2024)	Spain	KNN, RF, SARIMA	10-minute interval time series data from Murcia City	MAE, MAPE, RMSE, R^2	Deep learning model outperformed other techniques like RF, KNN, and SARIMA in prediction accuracy.
Görenekli & Gülbağ (2024)	Turkiye	ANN, RF, SVM, GBM	Historical data for 5000 water subscribers	R^2, MSE, RMSE, MAE	GBM achieved the highest performance with $R^2 = 0.881$.
Pourmousavi et al. (2022)	Iran	MLR, SVR, RF Regression	Annual residential water consumption in Isfahan	MAE, RMSE, MSE, R^2	MLR achieved 96% accuracy with <11% error; SVR achieved 95% accuracy with <13% error

Table 2. Devamı
Çizelge 2. Continued.

References	Region	AI Methods	Dataset	Performance Metrics	Results
Shirkoohi et al. (2021)	Canada	ANN, GA, ARIMA	Water consumption data from two cities -5 years and 23 months	RRMSE, Nash-Sutcliffe efficiency (E), MAPE	High accuracy for residential water consumption forecasting with <13% error rates.
Sajjanshetty et al. (2023)	Philippines	ANN	Income, rainfall, temperature, climate data	R-value, RMSE	ANN achieved high R-value of 0.97013 and low RMSE of 2.3463, effectively predicting Metro Manila water demand.
Al-Ghamdi, et al. (2022)	Saudi Arabia	ANN with PSO	Historical water demand and climate data (2004-2018)	RMSE	Hybrid ANN-PSO model achieved high daily water demand forecasting accuracy by optimizing hyperparameters.
Du et al. (2020)	China	Markov-modified ARIMA	Daily water consumption data from monitoring points	Relative Prediction Error (RE), R^2, RMSE	Markov-modified ARIMA corrected prediction errors and improved future forecasts over standard ARIMA.
Boudhaouia & Wira, (2022)	France	PR, NAR, SVR, MLP, LSTM	Internet-based platform providing daily water usage data	RMSE	NAR model achieved precise daily consumption predictions for residential (5 liters) and industrial facilities (23 liters).
Bhushan (2022)	India	LSTM, ARIMA	Sensor data	MAPE	LSTM achieved ~60% accuracy, outperforming ARIMA's 49%, demonstrating effectiveness with limited sensor data.
Gao et al. (2020)	China	UWM-ID	Water usage, weather, economic data, and water prices	MAE, RMSE	UWM-ID outperformed RF, MLP, and LSTM with 40%, 33%, and 20% improvements, respectively, across various test scenarios.
Zubaidi (2020)	-	Slime mould algorithm (SMA-ANN)	Monthly urban water consumption and climate data	MAE, MARE, MSE, R^2	The results highlighted the importance of data pre-processing to prepare the stochastic pattern of dependent and independent variables and to select the best scenario of independent variables.
Said et al. (2021)	Malaysia	DLNN-MLP, DLNN-CNN, DLNN-LSTM	Historical data based on the SIBU Division in Sarawak	RMSE	DLNN-LSTM (RMSE:0.051) can make decent predictions for water consumption time series despite being inferior to SARIMA (RMSE:0.183).

Artificial Intelligence Techniques and Algorithms in Studies

The most commonly used artificial intelligence models reviewed in this study were identified as Long Short-Term Memory (LSTM) models and Artificial Neural Networks (ANN), respectively.

Long Short-Term Memory (LSTM) Models

The studies analyzed in this review displayed the exceptional capabilities of LSTM models, mainly when applied to datasets with strong temporal dependencies. LSTM was developed by Hochreiter and Schmidhuber as a specialized type of recurrent neural network architecture (1997). The LSTM algorithm is highly effective in automatically extracting features from time series data and learning complex nonlinear relationships (Yu et al., 2019). Traditional recurrent neural networks (RNNs) produce effective results when working with data from the recent past. In contrast, LSTM models achieve more impactful outcomes with longer term data, such as months or years. In other words, LSTM models excel in utilizing large and complex datasets to deliver more accurate results. For instance, in the study by Kim et al. (2023) an LSTM model applied to water consumption data collected from different time intervals demonstrated exceptional performance, achieving low root mean square error (RMSE) values and high accuracy rate of 95%.

This study demonstrates that LSTM models were effectively utilized in both standalone (El Hanjri et al., 2023) and hybrid approaches (Boudhaouia & Wira, 2021; Kim et al., 2023; Liu et al., 2023). Standalone LSTM models learn from historical data to provide reliable predictions, while hybrid models combine LSTM with other algorithms to enhance accuracy (Boudhaouia & Wira, 2021). For instance, integrating LSTM with Particle Swarm Optimization (PSO) significantly reduced prediction error rates (Al-Ghamdi et al., 2022). However, it was also observed that LSTM models require substantial computational power to process large datasets and involve challenges related to generalization in certain scenarios (Bhushan, 2022).

Artificial Neural Networks (ANNs)

ANNs excel at identifying complex patterns and relationships within data, making them highly effective for tasks where traditional, non-AI models may struggle (Monjardin et al., 2020). Among these networks, methods such as Convolutional Neural Networks (CNN) (Cao et al., 2023), Feedforward Neural Networks (FFNN) (Oyebode, 2019), and Backpropagation Neural Networks (BPNN) (Huang et al., 2023) have been successfully implemented as standalone models for predicting water consumption.

Multilayer Perceptrons (MLP) were applied to predict urban water consumption based on meteorological data (Gao et al., 2020) and spatial clustering and water usage data (Yan et al., 2022).

In the studies included in this article, ANN models achieved high accuracy levels in predicting water consumption for different user groups. Specifically, when environmental factors such as rainfall, humidity, and evaporation are integrated into the models, these models produce more precise prediction results (Sajjanshetty et al., 2023).

Hybrid models

This systematic review examined studies utilizing individual and hybrid models of two or more AI applications. For instance, Al-Gamdi et al. (2022) applied the hybrid ANN-PSO model, while Zubaidi et al. (2020) developed and utilized a Slime Mold Algorithm (SMA)-ANN. Boudhaouia and Wira's (2022) study explored how ANN models can be combined with the SARIMA model to enhance water consumption predictions. The SARIMA and MLP hybrid models improved prediction accuracy by 4.6% compared to SARIMA alone, illustrating the enhanced performance of hybrid approaches.

Rustam et al. (2022) employed a novel machine learning approach to predict water quality and water consumption using various models, including deep learning models such as Random Forest (RF), Decision Tree (DT), Extra Trees (ET), Logistic Regression (LR), Support Vector Machine (SVM), and AdaBoost (ADA). As a result of the study, they achieved an accuracy of 0.96 in water quality prediction, outperforming existing studies in this field.

Said et al. (2021) found that integrating deep learning neural networks (DLNN) with MLP, CNN or LSTM models produced more accurate water consumption predictions compared to using these models individually. Furthermore, clustering algorithms and decision trees, when integrated with ANNs and SVM, were shown to enhance the accuracy of water demand predictions (Görenekli & Gülbağ, 2024; Oyebode & Ighravwe, 2019). Piasecki et al. (2018) compared the predictive performance of ANN and Multiple Linear Regression (MLR) models for estimating daily water consumption based on previous water usage and humidity records. The findings revealed that the ANN approach slightly outperformed the MLR model, achieving lower mean absolute percentage error (MAPE) value when an additional explanatory variable (humidity) was included in the ANN model. In summary, hybrid approaches can overcome the limitations of individual models, leverage the strengths of diverse methodologies, and provide deeper insights into the relationships between variables.

Performance Indexes

Performance indexes are statistical tools necessary to determine the predictive capability of an artificial intelligence model. They identify the error between the actual (measured) values and the values predicted by the model. In this way, they show how close the model's predictions are to the actual values. The indexes most commonly used in the studies included within the scope of this work are RMSE, MAPE, and R^2, respectively (Cao et al., 2024; Farah et al., 2019; Huang et al., 2023, Rustam et al., 2022).

RMSE is used to minimize the difference between actual values and predicted values. A low RMSE value indicates that the model's performance is excellent. MAPE, on the other hand, identifies the difference between actual and predicted values and expresses it as a percentage. The smaller the MAPE value, the better the model's accuracy (Willmott & Matsuura, 2005). The R^2 index measures the fit of a model to the data. It determines the relationship between the inputs (independent variables) and outputs (dependent variables). A high R^2 value indicates the model's accuracy and compatibility with the data (Willmott, 1981).

Pros, cons, and challenges of AI models

AI models can make accurate and reliable predictions for water consumption only by analyzing large datasets (Kim et al., 2013). These models are capable of identifying hidden patterns and trends in water consumption data. Moreover, AI models can be continuously updated with new data, enabling them to improve their performance over time (Huang et al., 2023).

In cases of missing data or uncertainty, hybrid and fuzzy models are highly effective tools for water consumption prediction (Yan et al., 2022). Thanks to their flexibility, fuzzy models can produce consistent predictions even when there are slight changes in input values. Additionally, they generate quick results with minimal processing time (Tzanes et al., 2023).

However, some models, such as ANN and DLNN, require large training and validation data. Additionally, these models may struggle with generalization, limiting their performance (Gao et al., 2020). While hybrid models like BSA-ANN and FFBP-ANN can improve predictions, they often have relatively slow processing times (Farah et al., 2019; Zubaidi et al., 2020). Although BPNN can accurately predict water consumption, it lacks generalization capability (Huang et al., 2023). Similarly, RF can become slow and less effective when a large number of trees are involved (Pourmousavi et al., 2022).

In summary several key considerations must be addressed to achieve highly accurate results with AI models for water consumption assessments. For example, researchers need to provide transparent information about the variables used in the models, the quality of the data, and the training process. Such openness will not only enhance the reliability of the studies but also reduce the likelihood of redundant research efforts.

DISCUSSION AND CONCLUSION

This systematic review highlights the role of AI in predicting water consumption and synthesizes recent studies from a methodological perspective. Unlike previous reviews, it identifies model-specific limitations, highlights gaps in application contexts, and integrates insights from hybrid modelling approaches while emphasizing the importance of developing low-cost and generalizable AI solutions.

Among the reviewed techniques, LSTM models achieved successful results in scenarios requiring time series analysis. This is because they accurately model long-term trends (such as annual increases and decreases) and seasonal fluctuations.

Indeed, this situation was clearly seen in case studies in the literature. For example, Kim et al. (2023) achieved an accuracy rate of up to 95% with an LSTM model trained with water consumption data collected at different time intervals. Similarly, Gao et al. (2020) reported that even under limited sensor data conditions, the LSTM model significantly outperformed the ARIMA model, which remained at 49% accuracy, with a prediction accuracy of approximately 60%.

The fact that LSTM provides such high accuracy is considered an important scientific finding.

These reliable predictions can be integrated into decision support systems in the field of water management, allowing resource planning to be optimized and proactive measures to be taken against demand fluctuations. In this way, the strategic steps required for the sustainable management of water supply-demand balance can be supported with more accurate data.

However, despite high accuracy rates for metrics such as RMSE and MAPE, these models face significant challenges due to their reliance on large data sets and extensive computational resources.

LSTM models typically require large amounts of data to make accurate predictions, which can negatively impact the performance of the models if sufficient and high-quality data is not available (El Hanjri et al., 2023). In addition, their complex algorithms require significant computing power (Boudhaouia & Wira, 2021). Working with large or complex datasets often requires robust hardware for training and operation. This can be a barrier to the widespread adoption of LSTM models.

Hybrid models are emerging as a highly effective and promising solution to overcome the limitations of single methods (Oyebode, 2019). Their ability to achieve high accuracy and adaptability results from combining the strengths of different AI models (Faiz & Daniel, 2023). However, hybrid models also have certain disadvantages. Problems such as slow processing times and increased complexity highlight the need to optimize hybrid models (Yan et al., 2022).

One of the key findings of this study is the critical importance of data quality and accessibility. When faced with incomplete or biased data, many models need help with generalization. Furthermore, most complex AI models are perceived as "black boxes", which makes their adoption by water management decision makers difficult (Wei et al., 2024).

LIMITATIONS AND FUTURE STUDIES

This systematic review has some limitations. First, the studies reviewed are limited to those published between 2019 and 2024. Studies about AI-based water consumption estimation published outside these years are not included in this review. Secondly, the data used in the individual studies comes from different regions or contexts. These differences make it difficult to directly compare the results of the studies. Furthermore the articles included in this systematic review used different evaluation techniques, such as water consumption or water costs, to measure the performance of the AI models. This diversity makes it difficult to determine which technique is most effective. Fourthly, all studies included in the review were written in English. Papers in other languages were not included in the research. Finally, this review does not include a meta-analysis due to the high heterogeneity of datasets, performance metrics, and study designs among the selected articles.

Future research should address several key aspects to bridge the gap in AI-based water use prediction studies and improve the studies in this field. The most important of these is the quality of the data to be used in the studies and the accessibility of the data. Good quality and sufficient data improve the training and output performance of the AI model. In addition, more work can be done on the integration of new AI algorithms. The development of interdisciplinary collaborations, e.g. between oceanographers, AI experts and legislators, will help to develop new models that will meet needs in the real world. Furthermore, more research on models that require low computational costs, i.e. less computing power and data, will help AI to be used effectively in areas such as sustainable water management. Although this review included studies from diverse application domains (e.g., residential, industrial, and urban settings), a detailed sub-analysis by domain was not conducted. Future studies may benefit from categorizing research based on application context to uncover domain-specific trends and challenges.

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