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Review

The Role of Smart Infrastructure in Residential Water Demand Management: A Global Survey

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Abstract

As the global demand for water rises and climate pressures intensify, projections indicate that water scarcity will impact nearly 40% of the world's population by 2030 and a quarter of all children by 2040. This study reviews the current literature on residential water efficiency, highlighting the most effective strategies for reducing water waste. A systematic literature review—guided by transparent criteria and quality assessments using the Critical Appraisal Skills Program (CASP)—was conducted to extract insights into water distribution management strategies. This study examines current smart water management initiatives aimed at reducing waste, with a particular focus on the policy and regulatory drivers behind global water conservation efforts. Furthermore, it shows innovative smart solutions such as Artificial Intelligence (AI)-powered forecasting, Internet of Things (IoT)-based metering, and predictive leak detection, which have demonstrated reductions in residential water loss by up to 30%, particularly through real-time monitoring and adaptive consumption strategies. The study concludes that innovative technologies must be actively supported and implemented by governments, utilities, and global organizations to proactively reduce water waste, safeguard future generations, and enable data-driven, AI-powered policy and decision-making for improved water use efficiency.

Keywords: water distribution; water management; smart water system; IoT-based network

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1. Introduction

In many parts of the world, water shortage is a major issue that has triggered social tensions and even conflict. A significant contributor to this crisis is the inefficient use of water, often stemming from a lack of awareness regarding its value and the essential services it supports. Increasing efficiency and productivity in water use is key to ensuring that future demand does not surpass the availability of water resources [1–6].

Water Distribution Management (WDM) has been the subject of several academic investigations from technological, social, economic, and legal points of view [7]. There are two main ways to approach the rollout of WDM programs: from a centralized or decentralized viewpoint. To optimize system performance, a centralized viewpoint often entails a command-and-control procedure in which one location reviews all relevant data and makes choices on behalf of all users. Users must comply with the instructions of the

control panel. To ensure fairness and widespread compliance, such systems may incorporate incentives or bonuses for select users. On the contrary, a decentralized viewpoint typically describes a bottom-up procedure in which users make choices independently based on their knowledge and then the decisions made by all users are combined to generate the system's overall performance. While centralized systems are generally considered more effective for optimizing performance, they are often less effective at fostering user participation and long-term adherence. In a nutshell, it is easier to implement and more efficient, but it is not always fair [7–14]. Drawing on well-established scientific literature emphasizing governance structure, efficiency, cost, user engagement, equity, resilience, scalability, environmental impact, and overall effectiveness, these criteria were selected to compare centralized and decentralized WDM systems. While efficiency and cost are crucial for assessing operational performance and financial sustainability [15], decision-making structure is a fundamental factor that affects the responsiveness and adaptation of water systems [16]. Fostering compliance and social acceptance, especially in diverse communities, requires user participation and a commitment to equity [17]. The system's capacity to adjust to external pressures and population expansion is addressed by resilience and scalability [18]. Environmental impact is also becoming more widely acknowledged for its role in resource recovery and sustainable development [19]. Lastly, when comparing WDM systems, these criteria are both thorough and supported by science where effectiveness acts as an integrative metric that captures total performance across technical, social, and ecological dimensions [20].

Table 1 provides a comparative analysis of both systems based on several criteria that have been considered due to review procedures.

Table 1. A comparative analysis of both systems based on several criteria that have been considered due to review procedures.

Criteria	Centralized WDM	Decentralized WDM	References
Decision-Making	Top-down, single authority	Bottom-up, individual users	[20]
Efficiency	High system-wide optimization	Moderate individual optimization	[21]
Cost	High due to infrastructure and management overhead	Lower upfront and operational costs	[22]
User Engagement	Low (limited user input)	High users actively participate	[21]
Equity/Fairness	May lack fairness due to one-size-fits-all mandates	High fairness through local customization	[23]
Resilience	Vulnerable to system-wide failures	More resilient due to Localized autonomy	[24,25]
Scalability	Scales well with central planning	May face challenges at large scale	[21,26]
Environmental Impact	May struggle with local sustainability and nutrient recovery	More adaptable to ecological design	[24,27]
Effectiveness	High effectiveness in control and consistency	High effectiveness in adaptability and resilience	[28,29]

Centralized WDM systems are effective and simpler to deploy in large cities with complex infrastructures, providing consistent management due to their hierarchical structure.

However, this top-down approach can limit user involvement and personalization, thereby constraining public participation [30,31]. In contrast, decentralized systems are often more resilient, economical, and equitable, particularly in diverse climates or smaller populations where community engagement is essential for effective water management [32,33]. While decentralized systems offer the potential for lower operational costs and improved local responsiveness, they may not achieve the same level of efficiency without proper integration and coordination, which can be challenging [34,35]. Moreover, centralized models can struggle with environmental sustainability and equity, as one-size-fits-all policies may not effectively address local societal needs and environmental challenges [36,37]. To balance responsiveness and control, a hybrid model that combines decentralized components with centralized oversight often emerges as the most effective strategy, enhancing flexibility, inclusivity, and adaptability while still ensuring optimal performance [38,39]. This integrated approach aims to effectively meet community requirements and technological demands, thereby fostering a more sustainable and equitable water management system.

While decentralized methods are frequently preferred in small or rural communities and centralized systems typically function best in major metropolitan areas, medium-sized cities—which are defined by diverse infrastructural capacity and economic levels—need hybrid approaches. Equity, affordability, and resilience can be improved in these situations by partial decentralization backed by centralized coordination. By adapting WDM tactics to local economic diversity, technology solutions are guaranteed to be available and efficient in a variety of socioeconomic circumstances.

However, water availability is a serious problem in many places of the globe. Nearly two-thirds of the world's population could be under "water stress" in the next decades, as the United Nations (UN) estimates that more than 2 billion people currently live in countries experiencing high water stress [40]. This is a particularly pressing problem in many countries in Africa and Asia, where people are expanding. Making better use of available water supplies is one approach to addressing this issue. This involves measures like reusing water sources and cutting down on waste. Many families waste water on non-essential uses like cleaning, bathing, and watering gardens, making residential usage a major contributor to water pollution. Studies indicate that households generate a substantial volume of polluted wastewater, with treatment plants in the United States processing over 34 billion gallons each day [41]. Human waste, food, and household products introduce nitrogen and phosphorus into wastewater, which—after treatment—is typically discharged into nearby water bodies, even though it could be safely reused for non-potable purposes.

However, water scarcity and water stress are often conflated concepts in water resource management literature, leading to suboptimal management plans. This paper explains the fundamental variances between these concepts and presents the Smart-MISS (Smart Multi-dimensional Integrated Scarcity and Stress) framework for full water resource assessment in residential buildings. The framework incorporates Internet of Things (IoT) technologies, Artificial Intelligence (AI) analytics, and multi-dimensional indicators to address scarcity and stress conditions instantaneously.

To explain these often-interchanged terminology, the following differences are presented to guarantee conceptual consistency throughout the work. Although the terms water shortage, water scarcity, and water stress are sometimes used interchangeably, they describe distinct concepts that are critical for effective water management. Water scarcity refers to an imbalance between available renewable freshwater resources and demand, typically quantified by per-capita renewable water availability. Values below 1700 m^3/capita/year indicate the onset of water scarcity, below 1000 m^3/capita/year indicate high scarcity, and below 500 m^3/capita/year indicate absolute scarcity [42–44]. Water stress, by contrast, focuses on the pressure exerted on water resources by human withdrawals relative to renewable

availability. It occurs when annual freshwater extractions exceed 25% of total renewable resources (moderate stress), 70% (severe stress), or 100% (critical stress), the latter indicating reliance on non-renewable sources such as fossil groundwater or desalination [43]. In such cases, they often rely deeply on non-renewable water sources or other supplies such as desalination, as understood in nations like Saudi Arabia, Libya, and the United Arab Emirates [45] The term water shortage is often used more generally to denote temporary or seasonal supply deficits, for example during droughts or infrastructure failures [46,47]. Clarifying these distinctions from the outset helps ensure that subsequent analyses and policy recommendations target the appropriate dimension of water challenges.

The Smart-MISS framework addresses the necessity for a complete, data-driven approach to consider and manage both water scarcity and water stress. Building upon intuitions and approaches demonstrated in the SEQ Residential End Use Study [48], the Smart-MISS framework incorporates the following:

- High-resolution data collection over smart metering to capture granular, time-stamped water use configurations.
- Behavioral and socio-demographic investigation to find high-consumption parts (e.g., small, older households) and patterns of incompetent usage.
- Disaggregated end-use modelling, allowing exact credit of demand to specific activities such as showers, laundry, and irrigation.
- Efficiency-based interference, including the elevation of water-saving applications and detection of non-compliant irrigation performs.
- Temporal demand profiling, using daytime water use patterns to update infrastructure design, peak-demand management, and strategy timing.
- Equity-aware design, accounting for varied local, demographic, and household characteristics that affect water stress levels.

By joining technical data with social and behavioral scopes, Smart-MISS provides a multi-layered and adaptive framework for analyzing and responding to both water scarcity (resource obtainability restrictions) and water stress (demand-driven pressure). This allows custom-made and actual water resource solutions at the household, regional, and strategic levels.

Table 2 summarizes the key variances and interrelations between water scarcity and water stress, sideways with the equivalent intervention plans proposed by the Smart-MISS framework.

Table 2. Water scarcity vs. water stress.

Concept	Definition	Key Thresholds	Main Drivers	Smart-MISS Response
Water Scarcity	Insufficient availability of renewable freshwater resources to meet wants	<1700 m^3/cap/yr (scarcity), <500 (absolute)	Climate, geography, and overuse of sources	Monitors obtainability, informs infrastructure resilience
Water Stress	Extreme pressure on available water resources due to extractions	>25% withdrawal (moderate), >100% (critical)	Population growth, lifestyle, and inefficient use	Targets mandate decrease, promote conservation behaviors

Numerous studies have examined strategies to improve domestic water efficiency and reduce wastewater [49–51]. For instance, some authors surveyed several programs designed to cut down on household water use in an article published in Water Research [52]. Low-flow showerheads, faucet aerators, and dual-flush toilets were among the treatments shown to dramatically cut water use. Chung et al. [53] conducted a literature assessment of research on the ecological effects of household water-saving technologies in another study [53]. In their research, they discovered that these tools had the potential to reduce

both water usage and Greenhouse Gas (GHG) emissions, but that the success of various interventions varied with parameters including geographic location, average family size, and the pricing of water.

Due to several variables, including population expansion and socioeconomic development, the frequency with which severe and frequent droughts occur, as well as the amount of water required by humans, has increased. Water supply utilities may follow the recommendations laid forth in adaptive water management plans during droughts, which address both supply- and demand-side issues. One common short-term demand-side strategy is restricting outdoor water use during droughts, which has been shown to effectively reduce consumption [54].

Life, ecology, agriculture, and economic growth all depend on water as a basic resource. Water shortage refers to the severe difficulty in obtaining sufficient clean, accessible water. It results from complex institutional, social, economic, and environmental factors. In some regions, water supplies are depleted due to pollution, overuse, or climate change. In others, scarcity stems from inadequate infrastructure, investment, or access—even when water is available. This complexity has led to multiple definitions of water shortage, each highlighting different aspects of the issue in Table 3.

Table 3. Water scarcity definitions across disciplines.

Definition	Definition Type	Source
When individuals lack access to sufficient, safe, and affordable water for personal or livelihood needs, the area is considered water scarce.	Access-Based	[47,55–57]
Scarcity occurs when aggregate user demands (including environmental) cannot be met due to limitations in supply or institutional arrangements.	Institutional/UN Definition	[58,59]
Defined by the marginal value of water, it is the opportunity cost of not having an additional unit of water.	Economic (Marginal Value)	[60]
There is insufficient water to meet all demands.	Physical Scarcity	[56]
Water is physically available, but access is limited by a lack of investment or institutional capacity.	Economic Scarcity	[47]
It is the yearly accumulated difference between daily water demand and availability. A persistent gap leading to resource depletion defines water scarcity.	Quantitative (Water Gap)	[61]
Water scarcity is shaped and often manufactured by political and institutional processes that marginalize certain populations.	Governance-Based	[62]

Based on the previous definitions, this study proposes the following definition which covers multi-dimensional disciplines including physical limitations, economic constraints, governance and political factors, environmental impacts, and quantitative indicators: “Water scarcity is a seasonal or ongoing situation where there is not enough water available in terms of quantity and quality to meet economic, environmental, and human needs.” Water scarcity results from a confluence of financial limitations, institutional or governance shortcomings, and physical deficiencies. It can lead to environmental deterioration, decreased agricultural output, health hazards, and social instability. It reflects not only biophysical imbalance but also social, political, and infrastructure injustices. This definition attempts to be operational, integrative, and policy-relevant, in line with both scholarly knowledge and practical difficulties.

The current definition describes a situation in which there is a need for water but not enough infrastructure to meet that need. When water is scarce because of climate or hydrology, it may be for brief periods of time and in extreme amounts. Water companies

often have contingency plans in place to deal with these kinds of water shortages. About 91% of the 483 utilities surveyed by the American Water Works Association (AWWA) had either a formal or an informal water shortage preparation strategy in place [63].

While it may seem reassuring that 70% of the Earth is covered by water, this abundance is deceptive; water scarcity is a growing global concern. According to UN projections, water scarcity could affect 40% of the global population by 2030 and one in four children by 2040 impacting both developing and developed nations [64]. Drinking water, as well as water suitable for agriculture, cooking, and bathing, is in short supply. The proportion of fresh water to total water on Earth is merely 3% [65], and the majority of that is either locked up in glaciers or otherwise inaccessible. While climate change and population growth are two of the most significant drivers, other human-caused challenges are also at play, such as pollution, conflict, deteriorating infrastructure and distribution networks, improper management of water resources, and overburdened water systems. Also, when water is scarce, sewage systems can break down, increasing the risk of water-borne diseases like cholera and typhoid. Worldwide, ecosystems are breaking down. As a matter of consequence, the cost of water rises, having an indirect impact on national economies. Here, the consideration of four distinct kinds of water that are often found in and around structures, most notably single-family homes, is illustrated in Figure 1.

Considering the building purpose, we are initiating water from the most rigorously tested municipal water supply system since it is the quickest, simplest, and most dependable option. Of course, there are many situations in which this water supply is not accessible. Most individuals do not give much thought to water storage or to the consequences of a water shortage. The quality and reliability of the water supply is also a major factor that must be considered.

Many factors contribute to poor water quality: chemical and physical characteristics; microbial composition (bacteria and photogenic organisms); and aesthetic qualities (color, odor, and turbidity) (pH, dissolved solids, disinfectants, etc.) [66]. The properties of rainwater, greywater, drinking water, and well water vary widely across chemical composition, microbial content, and sensory attributes such as turbidity and odor. Reclaimed water's acceptability is contextual and subjective [67]. Filtration may assist with this issue.

A review of global patterns reveals that different countries have used various strategies for agricultural water pricing. A nation's approach to agricultural water pricing is shaped by a combination of interrelated factors. These include the condition of its natural resources, particularly the availability of water, its historical patterns of water consumption and pricing, and the extent of its irrigation needs. Political and economic conditions, the development of social systems, and the significant share of water consumed by the agricultural sector also influence pricing decisions [68].

The growing emphasis on managing and preserving this scarce resource is largely driven by increased public awareness of national and international water regulations. Since agriculture uses large proportion of water, it has a significant say in what policies are developed to manage this resource. Water is an example of an input whose price is most efficient in case of equilibrium in demand and supply. The demand for water in a market is dependent on the final product's value, which in turn affects the product's price and total output. The ultimate price of water extraction affects the availability of that resource. The data warehouse stores data from all points in the supply chain (such as water sources and deposits, desalinization plants, and distribution networks) and makes it available to users in real time (with the option to customize data analytics) to aid in policymaking, pricing, risk management, and planning for water [69].

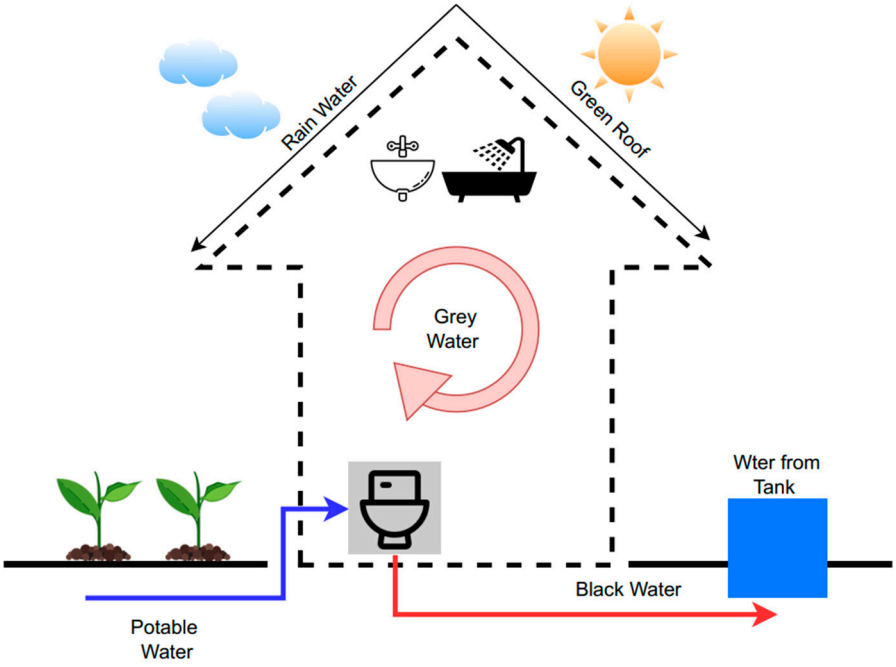


Figure 1. Sources of water at building level [67].

As a result, there is no universally accepted method of pricing or charging water in industrialized nations. This is because there is room for interpretation in the fundamentals, and also because water pricing systems are very context dependent [70]. Sustainable water pricing incorporates opportunity cost, efficient allocation, and environmental externalities to ensure long-term resource viability [1,71]. Many utilities use water pricing as a short-term economic tool within their demand-side management (DSM) programs to influence water consumption, supporting this broader strategy. For example, Reynaud (2015) [72] reported that a 10% increase in water prices could lead to a 15% reduction in household consumption, while [73] observed only a 6% decline, highlighting variability in pricing effects. This variation is largely due to the complex factors that shape the elasticity of water demand, such as indoor versus outdoor usage, seasonal fluctuations, socioeconomic disparities, and geographic context [74].

Conservation, public awareness campaigns, water pricing [75–77], and mandatory water restrictions are all common DSM strategies. These approaches form part of a broader demand-driven framework, which is considered an underutilized avenue for enhancing water sustainability [78]. This framework encompasses a wide range of policy tools, including economic pricing mechanisms, regulatory measures, engineering and technical solutions, the use of alternative water sources for non-potable applications, and public education and engagement [79]. Demand management can be further strengthened through initiatives such as water resource reallocation, revising irrigation water prices, upgrading infrastructure, and establishing water markets [80]. Experiences from various countries demonstrate that appropriate water pricing encourages responsible water use, whereas overexploitation often occurs in regions where prices are kept artificially low through subsidies [81].

Water costs are highest in industrial applications, followed by municipal and then agricultural uses. There are two main reasons why water remains undervalued: first, the high cost of transporting water limits the number of buyers and sellers in the agricultural sector; second, because water systems are shared, increased usage by one group raises marginal costs for all users. Water usage patterns across various building categories are summarized in Table 4.

Table 4. Water usage patterns across various building categories.

Influence Factors	Contents	Details
The external environment	Geographical environment Climate environment	Longitude, latitude, altitude temperature, humidity
Water supply and drainage system	Water supply and drainage facilities Water-saving measures Water supply and drainage management	Domestic water, irrigation water Reuse of recycled water and rainwater Management level, intelligent control system
Building design	Building design, shape, landscape	Various buildings like residential, commercial, and public buildings Shape, area, number of layers
Human dimensions	Life habit Other factors	Cultural qualities, energy-saving awareness, income

Using real-time data capture that can be saved and utilized in data analytics to conserve water effectively, water utilities have just recently begun to use smart water metering systems [82]. Advanced metering infrastructure (AMI), which may provide a remote link between water utilities, is one of the most important research areas supporting this trend [83]. Yet, there are a variety of ways to have that conversation: power fiber optics, cellphone transmission, broadband communication, and so on [84]. With the help of analytical software architecture, data from smart meters can be communicated with water utilities, allowing for more accurate monitoring and control of the system's water supply, as well as the issuance of timely alerts to warn consumers about their water usage and help them cut back [85]. It can also anticipate future water use based on past trends. There are many moving parts in the water system, from reservoirs to pumping stations to customer service. Precise forecasting should aid water utility management in preventing issues during periods of high demand or water loss [86].

The right data transmission method must be utilized when setting up a communications network for smart water meters. Choosing the right architectural and communication technologies may be difficult for water utilities due to the wide variety of alternatives available. These solutions vary in price, popularity, dependability, scalability, and security, among other metrics.

Water companies can use a multi-criteria decision framework, like the Best–Worst Method (BWM) put forth by [87], to execute the selection of communication technologies for smart water metering. This framework weighs the cost, reliability, scalability, security, and coverage of various alternatives, including PLC, NB-IoT, LoRa, Zigbee, and GPRS. Another case of the feasibility of a hybrid communication technique comes from the Alicante remote metering project in Spain, where GPRS was used for isolated or industrial meters and VHF radio modules (169 MHz) were used for congested urban areas. The combination revealed issues such signal gaps, interoperability, and societal acceptance in low-income areas while balancing network dependability, installation cost, and data continuity. Both studies shed light with evidence to the importance of mixing technical assessment and contextual adaptation in technology selection to ensure that communication systems continue to be reliable, reasonably priced, and inclusive in a variety of service contexts.

Integrating water services requires careful network planning to avoid interruptions [88]. Significant discrepancies in power consumption modeling have been the subject of many studies [89–91]. In contrast to water metering equipment, electricity meters may provide more detailed and accurate readings [92]. Although water use tends to be unpredictable, trends in energy consumption are often more easily identified and addressed [93]. Most domestic appliances' energy usage can be readily determined from their technical

specifications, but showers cannot, even within the same household [94,95]. Table 5 shows a comparison of measurement parameters of various techniques.

Table 5. Comparison of measurement parameters of various techniques.

Parameter / Study	[96]	[97]	[98]	[99]	[100]	[101]	[102]	[103]
Water Level	✓	✓	✓	✓	×	×	×	×
pH	×	×	×	×	✓	✓	✓	✓
Dissolved Oxygen	×	×	×	×	✓	✓	×	×
Turbidity	×	×	×	✓	✓	✓	×	×
Conductivity	×	×	×	✓	✓	✓	✓	×
Redox Potential	×	×	×	×	✓	×	×	×
TDS	×	×	×	×	×	×	✓	×
Chlorophyll	×	×	✓	✓	×	✓	×	×
Temperature	×	×	×	✓	×	✓	×	✓
Salinity	×	×	×	×	✓	×	×	✓
Flow rate (Litre/S)	×	×	×	×	×	×	×	×

It is evident from Table 5 that no experimental or measurable parameter is included in the research examined, even though flow rate plays a critical role in intelligent water management. This exclusion obviously indicates a research need, considering the significance of flow rate as a critical signal for leak detection, consumption dynamics analysis, and real-time water distribution optimization. The accuracy and reactivity of water management models are limited in the lack of flow rate data, which reduces their ability to support quick and data-driven decision-making. Therefore, future research should prioritize adding sophisticated sensor technologies and flow rate measurements to increase the operational and predictive capacities of smart water systems.

Optimizing the efficiency, sustainability, and dependability of water distribution systems is the goal of smart water distribution management, which makes use of cutting-edge technology and data-driven methodologies. These methods allow for proactive management of water resources by using real-time monitoring, sensor networks, data analytics, and automation. Water utilities can better identify and respond to problems like pipe breaks, leaks, and water quality issues with the use of smart meters, leak detection systems, and predictive modelling. Water conservation and reduced water waste should be encouraged with the use of demand management tactics like dynamic pricing and demand response, made possible by smart water distribution management. In sum, these methods provide water utilities with the means to make educated choices, boost system performance, and guarantee the supply of clean, safe water to fulfill the needs of expanding urban populations with little negative environmental effects.

IoT technology has been used in many contexts and is recognized as a critical enabler of Smart Cities. The data generated by IoT devices and our ability to make sense of that data have become more essential in recent years. These things will need an innovative and lightweight platform for the future supply of IoT services in order to comprehend data, exchange data, and share information and expertise. Interoperable micro-services, the granularity of heterogeneous objects, and virtualization via virtual object composites all provide support to the Web of Objects (WoO). Using a use case, ref. [104] proposed a WoO-enabled interoperable micro-services architecture for implementing the IoT of cross-domain applications. Ref. [105] developed a Smart City IoT platform using the micro-

service architectural paradigm. They argued that their paradigm had several advantages over the techniques used by competing architects.

Recent water conservation and development initiatives have centered on raising user-consumer awareness via the creation of intervention scenarios that instruct users on how to modify their usage habits. Intervention tactics that employ these technologies to educate clients and encourage behavioral changes, as well as short-term water use prediction and pattern recognition utilizing data mining and machine learning (ML) methodologies, have been the topic of recent studies [106,107]. For these types of interventions and warnings to work, it is essential to have an accurate, up-to-the-moment prediction of an individual's short-term consumption to use as a benchmark against longer-term goals [108,109].

Water demand forecasting has made use of several AI methods over the last few decades. Ref. [110] conducted an analysis of the studies conducted on the topic of AI-based water demand forecasting between 2005 and 2015. The authors discovered that the most often utilized methods were fuzziness detection, metaheuristic optimization, Artificial Neural Networks (ANNs), and Support Vector Machines (SVMs). Considering their hypothesis, ANNs were the most common technique for predicting future water needs [108,111]. Nonetheless, they determined that picking a single strategy as the best out of the many available is still challenging [110]. Researchers have highlighted that more work has to be done to improve water demand forecasting [112] despite the fact that AI approaches and their hybrids have been applied to the problem.

Machine learning (ML) algorithms have been heavily utilized by Smart WDM for forecasting water demand and anomaly detection. Each approach has different requirements for computation, accuracy of performance, input characteristics, and adaptability. To provide a clear comparison perspective, Table 6 lists the key findings and performance metrics of the primary machine learning approaches that have been reported in the literature.

Table 6. Comparison of ML Algorithms Used for Smart WDM Forecasting.

Algorithm/Model	Application Context	Performance Indicators	Strengths	Reference
VS-SVR	Dynamic daily urban water consumption forecasting	MAE = 5320.7 m^3/day; MAPE = 2.65%; RMSE = 7048.6 m^3/day; $R^2 \approx 0.93$	Dynamic model adapts to changing conditions; 33% RMSE reduction over static LSSVR	[113,114]
Deep Neural Network (LSTM-based)	Unsupervised anomaly detection in SWaT plant	Precision = 0.91; Recall = 0.80; F1 = 0.86	Fewer false alarms; captures nonlinear temporal patterns	[114]
SVM (Base Model)	Time-series regression	RMSE = 682.63; MSE = 467,214.38; MAE = 597.96; R^2 = 0.30; MAPE = 2.47%	Stable linear regression baseline	[115]
LSTM (Base Model)	Time-series regression	RMSE = 399.39; MSE = 159,519.52; MAE = 356.04; R^2 = 0.76; MAPE = 1.41%	Learns long-term dependencies; high accuracy	[115]
LSTM (Advanced + Moving Averages)	Combined time-series dataset	RMSE = 347.46; MSE = 120,731.41; MAE = 262.42; R^2 = 0.83; MAPE = 1.03%	Best overall accuracy; robust for multivariate data	
Backpropagation ANN	Short-term forecasting and classification	Accuracy = 68.6%; SD = 0.55; Time = 12.6 s	Fast convergence; simple architecture	

The analysis in Table 6 illustrates how updated development in machine learning has increased the precision and adaptability of smart WDM systems. Research using deep neural networks for anomaly detection shows that these models can capture complex, nonlinear, and time-dependent patterns in water distribution data, which can help reduce

false alarms and improve operational efficiency. In particular, the outcomes show that deep learning architectures particularly LSTM networks perform better than traditional models like SVM and ANN in terms of accuracy and robustness. Dynamic approaches, such as VS-SVR, further enhance prediction reliability through real-time feedback mechanisms, leading to lower error rates in comparison to static models. Overall, Table 6 tells that present progress in machine learning (ML) has increased the precision and adaptability of intelligent water demand management (WDM) systems which will motivate researchers to make more updates and create new algorithm which will help to improve water distribution management.

Muhammad and Feng looked at a number of AI methods for predicting city water use, including ANNs, fuzzy logic, extreme learning machines, and hybrid models including ARIMA and other statistical methods. For short-term water demand predictions, they found that AI technologies, particularly ANNs, performed better [116]. Papageorgiou [117] proposed a hybrid approach for time series prediction using ANNs and fuzzy cognitive mapping. Their proposed method aimed to choose the right connections and attributes for time series prediction following the training phase. They contrasted the expected daily water consumption value with the actual data in order to confirm the model's effectiveness. Shabani et al. proposed a SVM model based on polynomial kernel functions to predict monthly water use in a Canadian use case city. They intended to assess the phase space reconstruction prior to creating the input variable combination. They improved the SVM model's performance by lowering the latency [118].

Due to their extensive and versatile resources, cloud computing services have recently become a vital aspect of any contemporary system among organizations and people alike. With only cloud computing infrastructure capable of meeting the enormous computational demand, the challenge of maintaining an acceptable quality of service and Service Level Agreement (SLA) compliance may only increase [119]. Narayanan and Sankaranarayanan et al. [120] proposed an IoT concept for a subterranean water distribution system that makes use of Fog computing. The design of this smart city was based on predictions of future water use by its inhabitants. Daily demand over three months was predicted using ARIMA in their case study. Then, hydraulic engineers used an IoT architecture to create a water distribution system that wastes as little water as possible in the process.

Recent research demonstrated that fog computing performs better than standard cloud computing in a number of key areas. According to [121] fog computing processes data at the network edge rather than sending it all the way to distant cloud servers, which results in quicker reaction times, lower latency, and less bandwidth use. Fog systems are particularly useful for latency-sensitive Internet of Things applications because they provide more flexibility, improved security, and better resource management, according to their comparative research. These features ensure that real-time monitoring, quick anomaly identification, and uninterrupted operation even with intermittent connectivity in the context of smart water metering—demonstrating that fog computing is a more flexible and effective paradigm than traditional cloud systems.

Although the related work provides many soft computing methods for forecasting water needs, it cannot accurately model immediate needs. In addition, several ongoing studies attempt to predict future water use as a whole rather than identifying specific granular water needs [122]. The water needs of different areas may be managed using sophisticated and adaptable techniques that can adjust to the ever-changing behavior of individual users, but the literature did not provide means for fully integrated systems with online training and the opportunity to include cloud services [123]. A national-scale system proposing tiered infrastructure that can be developed to use all available ICT capabilities is, thus, required. There are alternatives to manual metering systems, and these include

smart water systems. The water meters in hundreds of homes are part of a wireless sensor network that sends periodic readings to a central database in real time [124]. Wireless water metering systems have been developed to some extent. The amount of water being utilized may be calculated with the use of flow sensors by the Smart Aqua meter [125]. ZigBee wireless technology is also used in the Wireless Smart Water Meter Reading System [126].

Lower network communication issues are resolved by the employment of technology at water meters, acquisition points, and data concentrators. In the higher network, GPRS transmission is used for communication between data concentrators and the data processing center [127,128]. Water temperature, phosphate, dissolved oxygen, conductivity, pH, turbidity, and water-level sensors may all be integrated into the "SmartCoast" Multi-Sensor System [129] for water quality monitoring. ZigBee communication is used so that the system may operate on the little amount of power needed in the deployment situation. Another method by [9] investigated the creation and evaluation of a real-time multi-sensor heterogeneous water monitoring system that was implemented in the River Lee Co. Water quality measurements in Cork, Ireland, including pH, temperature, conductivity, turbidity, and dissolved oxygen. The data was sent using ZigBee-compatible data telemetry systems and programmable System-on-Chip technologies.

One of the papers described the methodology focused on an autonomous measuring unit considering the usage of sensors to investigate water consumption related to GPS information. Due to its compatibility with both the GPS component and the water flow sensor, it was ultimately selected. A plastic valve body, a hall-effect sensor, a water rotor, and a water rotor make up the water flow sensor. Water flowing through the sensor rotor activates the sensor. The Hall Effect sensor detects variations in rotor speed caused by water flow and adjusts its output appropriately. The water sensor has a detection range of 1 m^3/min to 29 m^3/min with a detection accuracy of 1% [83]. Some authors suggested that questionnaires are helpful to manage and find out the existing smart technologies related to smart metering. According to [130], researchers in the field of engineering try to narrow down the possible sources of an effect to a manageable number of indicators or variables.

The proposed multiagent system is based on advanced forecasting techniques, including ARIMA models and NNs. Figure 2 illustrates the internal structure of the proposed multiagent model, highlighting the agents involved and their interactions [131]. Additionally, the study highlights the importance of maximizing water demand management (WDM), a rapidly evolving field driven by growing concerns about resource depletion and environmental degradation.

Another significant study gave the methodology for forecasting water consumption. The major goals of the water demand forecasting module were to determine the best water demand prediction model and to estimate the future water needs of households and farms [132]. The study developed a comprehensive assessment index for retrofitting existing residential buildings with water-saving measures, based on both local and international research findings. The assessment criteria and their weightings should be adjusted to reflect regional climatic and demographic conditions. Additionally, water efficiency should also be prioritized in the design and planning of new residential construction.

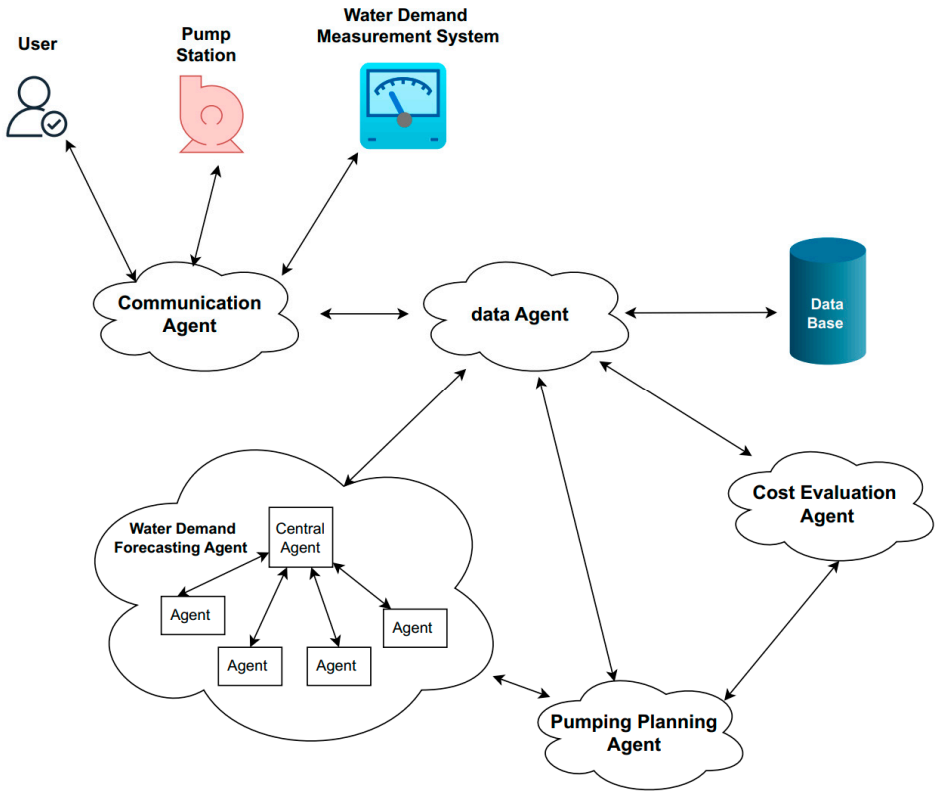


Figure 2. Multiagent system schematic.

Recent research is analyzed to assess the systems and strategies that enable efficient and cost-effective water use. Documented techniques for minimizing water use are reviewed and summarized for comparison. Drawing on a wide body of research, this review highlights practical interventions to curb residential water demand. The Methodology section outlines the research framework and scope of analysis. The next section presents an overview of earlier implementations of WDM strategies. Finally, the review highlights the role of smart technologies in WDM and explores the main technical barriers to their implementation. A concluding section ties together the findings and reflects on the broader significance of WDM strategies.

This study aims to present a thorough analysis of intelligent water demand management (WDM) techniques in residential buildings, emphasizing the incorporation of cutting-edge technology like artificial intelligence (AI) and the Internet of Things (IoT). Through creative, data-driven solutions that improve sustainability and efficiency, it emphasizes how urgent it is to solve global water stress and shortage. The paper is structured as follows: Section 1 introduces the background and importance of WDM, including key concepts and challenges. Section 2 outlines the research methodology, including research questions, search strategies, and quality assessment criteria. Section 3 discusses global motivations for implementing WDM, with emphasis on climate change, urbanization, and population growth. Section 4 evaluates the role of policies and regulations in facilitating WDM adaptation. Section 5 provides a critical assessment of current smart WDM technologies and implementation strategies. Finally, Section 6 presents the conclusions and reflections on the broader implications of WDM strategies for sustainable residential water management.

2. Methodology

This study examines WDM techniques in residential buildings using a methodical and organized review approach, focusing on how smart technology, legislative frameworks,

and sustainability issues are integrated. In order to overcome earlier constraints regarding selection bias, quality evaluation, and data synthesis, the technique was created to guarantee transparency, reproducibility, and scientific rigor.

2.1. Research Questions

The review is controlled by three main research questions (RQs):

RQ1: What is water distribution management (WDM), and how has smart WDM evolved or been conceptualized in previous research?

RQ2: What values and economic implications are associated with smart water management systems in residential buildings, and what technologies enable their implementation?

RQ3: What are the key benefits, challenges, and policy considerations associated with deploying smart WDM strategies?

2.2. Literature Search Strategy

A thorough literature search was carried out using ScienceDirect and Scopus databases. We conducted the search between January 2010 and December 2023. With a residential focus, the search approach included sustainability, technology, and regulatory issues. The subsequent combinations of keywords were employed:

"water distribution systems" AND "building",
"water supply systems" AND "residential",
"water management" AND "residential buildings",
"smart water" AND "residential buildings",
"policy and regulation" AND "residential",
"sustainability", "Internet of Things" AND "residential",
"artificial intelligence" AND "residential",
"big data" AND "residential",
"blockchain" AND "residential".

The search was limited to peer-reviewed, English-language journal articles using Boolean operators and filters. In order to find more pertinent research, the reference lists of important publications were also manually examined. Peer-reviewed empirical research, review papers, or technical reports that addressed WDM or smart water technologies in residential or building-scale contexts and were published in English between 2010 and 2023 met the inclusion criteria for this study. Non-peer-reviewed literature (such as blogs or opinion pieces), conference abstracts or poster summaries, and studies that were not pertinent to residential settings were excluded. Two phases of screening were applied to the articles: (1) screening by title and abstract and (2) full-text evaluation. Two reviewers separately conducted each viewing. Discussions or third-party adjudication were used to settle disputes. The Critical Appraisal Skills Programme (CASP) instrument was used to assess methodological quality and bias risk. Clarity of objectives, appropriateness of technique, rigor of data collection, and consideration of limits were among the CASP criteria used to evaluate the studies. A quality rating (good, moderate, or low) was assigned to each study. Each included the study's authorship, publication year, country of study, research aims, methodology, technologies, or policies addressed, and important findings were gathered using a standardized data extraction form. To reduce bias, two reviewers separately extracted the data. Using a narrative theme approach, the findings were synthesized and arranged into four main categories: environmental effect, user involvement, technology deployment, and governance and regulation. When appropriate, results from several investigations were compared using tables and matrices. To guarantee repeatability, the review approach was well documented, including the search strategy, keywords, inclusion/exclusion criteria, and data extraction techniques. Every choice made

throughout the screening and quality assessment processes was recorded, and any disputes were openly settled using a methodical review procedure. Figure 3 shows how the number of publications about WDM and associated smart technologies has been increasing over time. Growing scholarly and practical interest in sustainable water solutions for residential structures is shown in the graph's notable growth in research output, especially after 2015. This pattern emphasizes how urgent it is to solve WDM issues through legislation, innovation, and technological integration, all of which are examined in this paper.

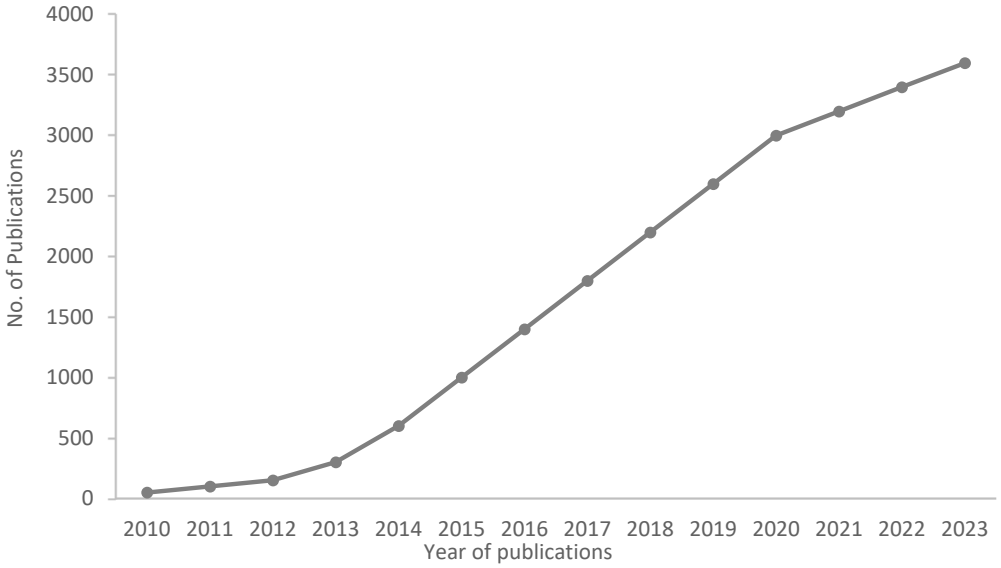


Figure 3. Publications in WDM.

The scope of this review was restricted to peer-reviewed, English-language research that was obtained from ScienceDirect and Scopus, guaranteeing data quality and methodological consistency.

In addition, the Smart Multi-Dimensional Integrated Scarcity and Stress Framework (Smart-MISS) has been used as a conceptual basis to guide the selection and selection process. It integrates technical, behavioral and political dimensions for comprehensive assessment of water scarcity and stress in the home context. This framework has shaped the formulation of key words, inclusion criteria and thematic categorization, ensuring that the reviewed studies are consistent with the multidimensional focus on data-driven metering, behavioral analysis and water management strategies that are equity-based.

Figure 4 illustrates the systematic selection process for identifying relevant academic publications from search engines. A total of 435 records were initially identified. After title and keyword screening, 273 records were excluded (267 for irrelevance and 6 for missing details), leaving 162 records for abstract screening. During the abstract screening stage, 62 records were excluded for irrelevance, resulting in 100 records proceeding to full-text screening. After the full-text review, 48 records were excluded for irrelevance, leading to 52 academic publications being finally included for review.

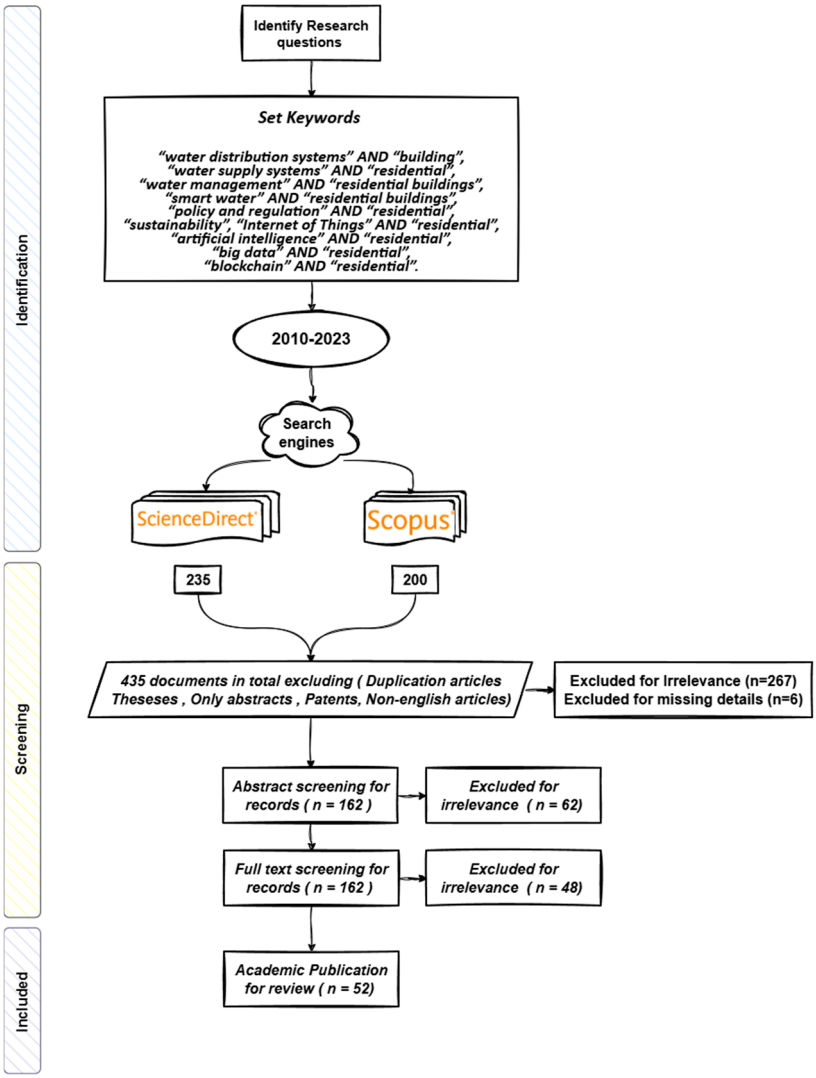


Figure 4. PRISMA diagram showing number of records identified, screened, excluded, and included.

3. Global Motivations for WDM

Effective water management is essential since water is a resource necessary for human survival. Both the significant shift in weather patterns and the exponential rise in human population have resulted in a shortage of available water. With rising demand, the government and water utilities face a growing problem in water management. Providing high-quality water while reducing expenses and energy use is another obstacle. Water consumption, agriculture, food production, the environment, and other facets of human life all depend on effective water management. This may be achieved with the help of smart water analytics, which prioritizes real-time data collection and presentation so that analysts can focus on analysis and action in a timely and cost-effective manner. Real-time water monitoring, leak detection in distribution systems, and water quality monitoring and maintenance are all part of an SWM system.

3.1. Overview

Water management has received growing attention in the 21st century due to urbanization, population growth, and environmental degradation affecting water quality [133]. Supply-side solutions—such as water diversion, wastewater recycling, desalination, rainwater storage, and virtual water imports—have long dominated efforts to address water issues [81,133]. By the early 2000s, over 3300 water recycling projects had been launched

globally, including 200 within the European Union. Desalination offers a way to address water scarcity but requires high energy inputs [134]. More than 12,500 desalination units were in use in 120 different countries in 2006 [81] but existing methods are insufficient for long-term water sustainability because they fail to prevent water loss. As a result, WDM is essential for reducing consumption and promoting long-term sustainability.

While supply-side measures are important, demand management is essential for the efficient use of water. WDM aims to promote water-saving behaviors among users. Tortajada and Joshi emphasize that public participation must be both encouraged and enforced for effective demand management [135]. Public policies and political decisions also shape both water supply and demand management. For instance, water issues might be either worse or improved upon depending on the water price regulations in place. In regions such as North Africa, underpricing water below its recovery cost often leads to overuse and pushes consumption beyond sustainable limits. Achieving effective demand management also depends on strong institutions, a skilled workforce, clear legislation, and sustained political will [135].

3.2. Role of Policies and Regulations in WDM Adaptation

WDM relies heavily on policies and regulations to function properly. Public health, economic growth, and environmental sustainability are all impacted by the infrastructure that delivers water to homes and businesses. Public and private water suppliers are held to the same quality standards set out in policies and laws. The treatment, testing, and reporting of water quality may be subject to these guidelines. Water quality and safety may be guaranteed for the public by implementing these regulations. The World Health Organization (WHO) stresses the need for legislation to ensure safe drinking water. "Policies and regulations play a critical role in ensuring the provision of safe drinking water," the WHO notes [136]. Models that quantitatively describe how water demand is influenced and varies in relation to exogenous uncontrolled drivers (e.g., seasonality, climatic conditions) and demand management actions (e.g., water restrictions, pricing schemes, education campaigns) are essential to explore water users' response to alternative WDM, ultimately supporting strategic planning and policy design [137]. Water consumption limitations, the promotion of water-saving technology, and incentives for water-efficient activities are all examples of policy and regulation's ability to encourage water conservation. Policymakers may reduce the need for expensive modifications to the water system by encouraging water conservation [138,139].

During times of drought or scarcity, policies and regulations can aid in water management by limiting water use and establishing rules for water allocation. Fair and sustainable water distribution to homes, companies, and farms is possible with careful management of water resources. The relevance of policies and regulations in water resource management is highlighted by the Organization for Economic Cooperation and Development (OECD). "Effective water management requires robust policies and regulations," OECD notes [139]. Water Tariff mechanisms and rates for water consumption may be set by policies and laws, with the proceeds going toward water infrastructure upkeep and development. Rates and fees may be adjusted to encourage less wasteful water consumption and boost conservation efforts. Tariff-setting regulations are emphasized by the International Water Association (IWA) as crucial to the long-term viability of water distribution networks. "Effective tariff-setting policies can help to ensure that water services are financially sustainable," IWA states [140]. Mechanisms for setting water prices vary greatly depending on the political system, the availability of resources, and community norms. Although cost recovery is still a prevalent topic across the nations under consideration, there is a growing tendency toward combining social and environmental goals. Block tariffs and scarcity-linked fees

are examples of incentive pricing that is growing in popularity. However, there are still issues with maintaining infrastructure, guaranteeing equity, and adjusting to water stress brought on by climate change. Table 7 summarizes the key water tariff mechanisms, along with their definition.

Table 7. The key water tariff mechanisms, along with their definition.

Tariff Mechanism	Definition	Purpose/Rationale
Fixed Charge	A constant fee is charged regardless of consumption	Ensures basic revenue for utility
Volumetric Pricing	Users pay per unit of water consumed	Promotes conservation, links cost to use
Increasing Block Tariff (IBT)	Price per unit increases with higher usage (e.g., blocks of m^3)	Encourages conservation, supports equity
Decreasing Block Tariff	Price per unit decreases with higher usage	Favors large users, promotes economies of scale
Two-Part Tariff	Combines a fixed charge and a variable (volumetric) component	Balances cost recovery and consumption-based billing
Seasonal Tariffs	Higher rates in peak season (e.g., summer), lower in off-peak	Reflects supply stress and scarcity during certain times
Quota-Exceeding Tariff	Users are allocated a quota, with higher rates above that	Discourages overuse beyond "essential" need
Flat Fee	Single fixed amount per month, regardless of use	Simplicity, but lacks conservation signal
Free Allowance/Lifeline Tariff	The initial volume of water (e.g., 10–20 m^3) provided at low or zero price	Basic human rights, affordability
Marginal Cost Pricing	Price reflects long-run marginal cost of water provision	Economic efficiency, cost-reflective pricing
Market-Based Pricing	Water rights or permits are bought and sold	Reflects true market value, allocates efficiently
Subsidized Block Pricing	Lower prices for lower-income households in initial block	Promotes affordability and equity
Index-Linked Tariffs	Tariffs adjusted regularly based on inflation or cost index	Keeps tariffs sustainable over time
Wastewater Tariffs (Add-on)	Separate charge for wastewater treatment	Ensures environmental cost recovery
Pollutant-Based Charges	Fees based on volume and concentration of pollutants discharged	"Polluter Pays Principle", incentivizes cleaner processes

However, the physical and technological features of the water system influence water pricing systems. The degree of water scarcity, the geographical distribution of demand, and the natural freshwater availability all have a direct impact on the cost and structure of water service. The amount of capital and operating costs that must be recouped through price depends on the distribution, transmission, and treatment infrastructure's efficiency as well as its existence. Pricing must take maintenance and rehabilitation requirements into account when infrastructure is old or has significant leakage rates. Tariff levels are also greatly impacted by expensive and energy-intensive procedures like desalination, wastewater treatment, and long-distance water transportation. As a result, pricing methods are frequently designed to represent the true costs of providing water.

Water pricing policy creation and implementation heavily rely on institutional and governance frameworks. The degree of decentralization in water management, the ability of regulatory agencies, and the presence of explicit legislative frameworks are a few

examples. Pricing practices' uniformity and equity are impacted by the division of duties between national, regional, and local organizations. However, institutional capability alone is not enough to ensure the effectiveness of such institutions; political stability and commitment are also necessary. When moving from heavily subsidized models to cost-reflective alternatives, policy reform initiatives may encounter opposition from the public or political constraints. In order to execute sustainable and widely accepted pricing plans, effective leadership and stakeholder involvement are therefore crucial.

Despite considerable global regulatory advancements, integrated digital systems are still less common in policy frameworks than supply-side governance and tariff reform. To secure interoperability of smart-meter data and put WDM legislation into effect, governments ought to act on data-sharing guidelines for utilities, municipalities, and environmental organizations. While protecting affordability for low-income households, dynamic block tariffs connected to real-time usage data might incentivize conservation. Furthermore, policymakers should secure a grant program for capacity-building initiatives that educate regional water authorities how to use incorporate AI-powered forecasting tools for flexible water distribution. Additionally, behavioral incentives may be matched with regulatory goals through public engagement tools, including mobile dashboards that display home consumption vs. community targets. By using these steps together, policy frameworks are move from rigid rules to flexible, data-driven governance structures.

Water price systems are also heavily influenced by socioeconomic factors, cultural norms, and environmental factors. Progressive tariffs, targeted subsidies, and affordability assessments are used to balance the need to recoup expenses with the capacity of customers to pay for water services. The price must also take into account how the general public views water, particularly in areas where it is considered a fundamental human right since this might affect their willingness to accept new price changes. Furthermore, price systems that internalize external costs are becoming more and more necessary due to environmental considerations including pollution management, ecosystem conservation, and resource sustainability. More responsible water usage is facilitated by mechanisms that take resource scarcity, seasonal demand, and wastewater discharge into consideration.

To have a better understanding of the global implementation of water pricing regimes, Table 8 presents a comparative comparison. Key factors across nations are outlined in this comparison, such as price foundation, sectoral coverage, cost recovery emphasis, integrating social and environmental goals, and the primary difficulties faced. Highlighting both standard procedures and situation-specific strategies, the goal is to provide a systematic summary of the many ways that different elements affect water price policy in various countries.

Several important factors are included in the comparison table to examine water pricing strategies in various nations. The term "country" describes the national setting in which the pricing system functions. Pricing Basis shows if the structure is market-driven, decentralized, or centralized. The pricing system's primary users, such as the domestic, agricultural, or industrial sectors, are identified by the Main Sectors field. The degree to which the pricing attempts to recoup all capital and operating expenses is reflected in the Cost Recovery Focus. Environmental Pricing indicates if tariffs include costs for pollution, conservation incentives, or resource shortages. Social Equity Consideration assesses the presence of mechanisms to support affordability and protect vulnerable populations. Lastly, Key Challenges lists the main obstacles or constraints encountered when putting into practice sustainable and successful pricing strategies.

Table 8. Comparative analysis of water tariff systems and policy focus by country.

Country	Pricing Basis	Main Sectors	Cost Recovery Focus	Environmental Pricing	Social Equity Consideration	Key Challenges
Australia	State-based, national framework	Urban, irrigation	High	Medium	Medium	Variability, drought regulation
Brazil	River basin (ANA)	All	Medium	Low	Medium	Regional disparities
Canada	Local/province	All	Low to Medium	Low	Medium	Low price incentives
Chile	Market-based	Urban, agriculture	High	Medium	Low	Groundwater management
China	Central and local hybrid	All	Medium	Low	Medium	Institutional overlap
Colombia	Centralized (post-1994)	All	High	Low	High	Implementation of tariff reforms
France	National system	Urban, agriculture	Medium	Medium	High	Pricing complexity
India	State jurisdiction	Irrigation, urban	Low	Low	Medium	Low pricing efficiency
Italy	Decentralized	Urban, industry	Medium	Low	Medium	Investment support via taxes
Mexico	Regional zones	All	Medium	Medium	Medium	Sector equity
Netherlands	National taxes + pricing	Domestic, industry	Medium	Medium	Medium	Fiscal efficiency
New Zealand	Local control	Urban, irrigation	Low to Medium	Low	Medium	Irrigation water scarcity
South Africa	National + local tier	All	Medium	Medium	High	Implementation & affordability
Spain	National + EU directive	All	Medium	High	Medium	Climate adaptation, CAP linkages
Saudi Arabia	Nationally regulated	Urban, agriculture	Low	Low	High	Heavy subsidies, low tariffs
GCC Countries	National frameworks	Urban, agriculture	Low	Low	Medium	Low-cost recovery, high consumption
Egypt	Centralized	Urban, agriculture	Medium	Low	High	Low tariffs, high subsidies
Yemen	Local corporations	Urban, agriculture	Low	Low	Low	Weak enforcement, over-extraction

Because increasing block tariffs (IBTs) can strike a compromise between social justice and water conservation, they are one of the most often suggested price systems. Water shortage is further addressed by implementing seasonal and quota-exceeding fees, which lessen the strain on infrastructure during times of high demand. Two-part tariffs, which include fixed and variable costs, are frequently employed to preserve utility income stability and guarantee equity. In certain situations, market-oriented techniques have been implemented to improve allocation and efficiency, especially in systems where water rights are transferable. In order to safeguard vulnerable and low-income groups, social tariffs and tailored subsidies are also commonly used, guaranteeing affordability without sacrificing environmental objectives.

Equality of access to water may be ensured by the implementation of policies and regulations that define guidelines for connecting new customers to the water distribution

system and provide financial help to low-income families who struggle to pay for water services. The UN General Assembly has acknowledged the significance of laws and regulations in guaranteeing people's fair access to water systems. The UN General Assembly recommends that "governments should develop and implement policies and regulations to ensure that everyone has access to safe, sufficient, and affordable water services" [141].

4. Assessment of Current Techniques in Smart WDM

Water utilities may improve their processes and cut down on waste by using ML algorithms to estimate water demand based on historical data and weather predictions [142]. Large datasets from water distribution networks may be analyzed using big data analytics to reveal patterns and trends. Optimizing system performance, finding leaks, and anticipating equipment breakdowns are all possible with this information [143]. Data from water distribution systems may be securely stored and processed on the cloud, making it possible for utilities to evaluate the data in real time from any location. Utilities will be able to make better judgments on system operations and maintenance using this information [144]. Multiple parties, such as utilities, regulators, and customers, will have access to this information, fostering greater openness and accountability [145].

The open-source software "Smartin" is developed by hypothetically retrofitting an Alpine municipality with smart rain barrels (SRBs) to evaluate the effects of the latter on the urban water infrastructure. Compared to uncontrolled rain barrels, a simple coordinated control strategy already clearly improves the performance of the integrated system by reducing combined sewer overflow and addressing drinking water demand. "Smartin" can be used for modelling the real-time control of micro storages developed as an IoT-based solution in a coupled model of urban drainage and water supply systems [146].

New methods are introduced in this section from various studies. A controller will monitor each building's energy use and regulate the supply lines. The controller will notify the Solenoid controlled water flow transmitter when a user's allotment has been depleted. The pricing for each organization will be determined, and the results will be uploaded to the cloud. Similar information may be retrieved from the cloud and kept on display for locals through a web portal. Using this online tool, the system may become more understandable to users. The water consumption limit, for instance, is very sensitive to factors such as the amount of water in the dam. These portals display the current water level in the dam, relieving citizens' concerns about being shortchanged when their allotment of water is cut.

One of the articles [113] describes a method for creating accurate predictions using a nonlinear, adaptive Support Vector Regression (SVR) model. The accuracy performance for optimum management of urban water resources supply was enhanced by the findings of the suggested Variable-Structure Support Vector Regression (VS-SVR) model technique. As described by [147], keeping an eye on water use trends may help businesses run more smoothly and effectively. The authors elaborated on how dispersion analysis of flow patterns was compared to actual customer meter readings. According to [148], demand-based pricing is an effective technique for modifying consumers' water use patterns over the long run. If every home had a smart water meter, [149] reasoned, time of use tariffs (TOUT) could be put in place to either penalize users for exceeding a daily consumption threshold [150] or reward them on a monthly basis. Creating a real-time web-portal visualization tool to show consumers where and when their water is being used would be a huge help in rolling out TOUT [151]. Consumers may be encouraged to decrease or shift their demand at peak times via the use of pricing, incentives, and informative tools.

Many academic studies [152–155] and recommendations about household water use have been published. Nevertheless, these studies vary greatly in terms of methodology, data, geographical resolution, temporal resolution, and clustering technique. Several of

them rely on questionnaire data [156], which has been criticized for its lack of reliability, precision, and generalizability. The accuracy of studies that use actual water use data is higher. This study, which is undertaken over the course of a year and covers an area of a district or a city, has shown promising findings [157–160]. Yet, the timeframes involved in such studies are enormous. Although some studies have been conducted on an hourly time frame, these studies have often only analyzed the water consumption volume of a single user's habits, such as taking a shower or making a meal [157,161,162]. Rare are the studies that take advantage of big consumers' hourly water use data.

In order to reliably anticipate leakage, systems that rely on pressure monitoring need to maintain relatively consistent pressure levels throughout the system's operation. An IoT system that alerts both administrators and end users upon detecting leaks and poor water quality is offered as a viable option [163]. There is a proposal for a synchronization node between flow rate nodes, which would allow for real-time leakage detection using an economical set of measurements. Exploring water users' response to an alternative WDM system, which in turn supports strategic planning and policy design, requires models that quantitatively describe how water demand is influenced and varies in relation to exogenous uncontrolled drivers (e.g., seasonality, climatic conditions) and demand management actions (e.g., water restrictions, pricing schemes, and education campaigns). To begin with, the list of objects that need to be online is quite broad, including people, pets, household gadgets, cars, and more. Second, the sensing layer is equipped with a variety of sensors and transducers. Sensor and actuator nodes are controlled by microcontrollers like Arduino and Raspberry Pi, which make up the sensing and actuation layer. Third, the layer of the network via which sensing signals are sent to a server or the cloud is detected. In IoT, data is shared between individual devices and their network neighbors and/or cloud-based services through various communication modules [164].

One of the most promising solutions for alleviating water shortage in populated areas and rural communities is the regulation of household water consumption. The employment of antiquated techniques at the family level, such as touring residences and reading water counters, creates difficulties in water management. One of the reasons there is no sustainable economy is because of a lack of proper home water use monitoring and water forecast [165]. Household consumption ranks second among the two primary water usage reports recorded by the National Institute of Statistics of Rwanda [166]. Moreover, as the global population rises, so too will the need for fresh water. According to the WHO, one in three people on the planet suffers from water scarcity [167,168]. Thus, water stakeholders and policymakers throughout the globe maintain pushing for household-level water management [169,170] in order to control water resources by assessing a variety of characteristics that have an effect on families [171]. It is not likely that other technologies, such as AI and ML, which can help in forecasting water demand by evaluating related parameters like the population growth rate of the region where water is being supplied, will be integrated due to the lack of digital data about water usage. This really makes an impact on the WDM for confirming the availability of the system. Each home is fitted with a smart water meter and dealt with a dynamic pricing system in the water distribution system, with the goal of monitoring and predicting water use during peak demand hours.

Pricing techniques were the primary focus of these studies. In addition, a smart water meter was used to calculate water wastage in the studied network. The study's methodology relied only on measuring water loss in a network's distribution system and tracking people's individual usage [172].

Wear and tear on water distribution networks need precise, real-time evaluation and monitoring for optimum performance. Typical manifestations of damage include pipe breakdown episodes that result in high quantities of nonrevenue water (in the 20–30%

range) [173]. Consumption is often averaged over a period of time and then compared to the same time period in the past to spot discrepancies. This approach does not allow for real-time processing, does not account for drifts, and does not adjust to variations in the time series. As decisions are sometimes made in real time, it is crucial that anomaly detection algorithms can be implemented in that time frame. As water meter readings may be interpreted as time series, change-point approaches are well-suited to the task of anomaly identification. In research, such techniques enable us to tell apart between two types of anomalies: a break in the signal [173] (a change in the consumer's water usage habits) and an abnormal rise in the signal (water loss incidents). The use of probabilistic outlier identification in water management [114] has also been investigated. Data probability distributions are needed for this, with low-probability data points being deemed anomalous. A Deep Neural Network (DNN) that has been taught on typical data may serve as a representation of this probability distribution. In another study, a method is described for determining the optimal neural network design for a given dataset via the use of gas [114]. The authors employ exponentially weighted moving average smoothing, the mean p-powered error measure, separate error weights for each tag value, and separate prediction windows to lower the false negative rate.

One of the synthesis pieces delves into the idea of "smart water grids" and how they may be used to enhance WDM. The need for real-time monitoring, leakage detection, and demand control via sensor networks, enhanced metering, and data analytics is emphasized [174,175]. This really ensured an impact on WDM and increased the possibility of using WDM in the future. Using examples from water quality monitoring, leak detection, and demand forecasting, ref. [176] describe the use of IoT technology in WDM. IoT's potential to improve water distribution efficiency is highlighted. The influence of SWM technology on WDM is examined in another review study. It explains how the IoT, AI, and data analytics may be used to enhance water distribution networks, boost water quality, and cut down on water waste [177].

Table 9 summarizes key methods and technologies used in smart water distribution systems. It includes applications of IoT, AI, and advanced metering systems that collectively enhance monitoring, forecasting, and efficient water use in residential and utility-scale settings.

In some other research, authors suggested the SRB which is an IoT-based solution for urban water management with micro storages developed system. The SRB is essentially an enlarged rain barrel with an electrically operated discharge valve. This idea provides (1) granular control over each SRB via its absorption into the management of the whole water system, and (2) easy, widespread deployment of additional storage units in lieu of costly, time-consuming, and invasive infrastructure expansions. Smartin, an open-source program, used to simulate the potential retrofitting of an Alpine town with SRBs and assess the latter's impact on the city's water system, was built using this scenario. The performance of the integrated system is improved by lowering combined sewage overflow and meeting drinking water demand with only a basic coordinated management method, as compared to unmanaged rain barrels [146]. Table 9 shows the smart water distribution methods based on various key points.

Table 9. Smart water distribution methods.

Key Points	Definitions	References
IoT-based system	There are alternatives to manual metering systems, and these include smart water systems. These are examples of wireless sensor networks, in which water meters in thousands of homes gather data at regular intervals and relay that information in real time to a central database. Water temperature, phosphate, dissolved oxygen, conductivity, pH, turbidity, and water-level sensors may all be integrated into the "SmartCoast" Multi-Sensor System for water quality monitoring. ThingSpeak is a cloud-based IoT analytics solution that enables the collection, visualization, and analysis of real-time data streams. The ThingSpeak platform provides access to MATLAB analysis, which computes statistics like the lowest, maximum, and average amounts of water consumed daily, weekly, and monthly.	[125,178,179]
AI-IoT–enabled WDS	Building managers can keep tabs on water use and demand, as well as examine the efficiency of their water systems, with the help of AI-enabled IoT water management systems. The water quality index fluctuation can be explained by the Support Vector Machine (SVM) models 87% of the time. SVM's findings may potentially be used to better manage rivers to ensure a high-quality water supply. In Ohio, USA, AI is used in conjunction with IoT data on water levels, flow, and storage capacity across stormwater and combined sewer collection networks to create a wet weather management system. This aids in the monitoring of utility networks and the optimization of storage capacity to avoid floods and overflows during rainy weather events.	[180–182]
Water Smart meters	The smart water meter's prototype includes a microprocessor, a Wi-Fi module, a water flow sensor, and a GPS module. One of the most well-known and widely applied stochastic time series models, the autoregressive integrated moving average (ARIMA), captures a variety of common temporal features in time series data. When it comes to fine-tuning Holt's Winter method's coefficients, deep learning techniques like the Recurrent Neural Network (RNN) and its variant, the Long Short-Term Memory (LSTM), are able to learn predictions from sequences of data.	[115,183–186]
Efficiency in IoT technology	From the outset, power is fed into the system from the generator. When the ultrasonic sensor has been properly calibrated, the system may begin functioning. A model of a physical system that is stored digitally. Clustering and Kohonen networks are used in an integrated water and energy forecasting model to provide accurate predictions of future water and energy needs.	[187]
Application of AI in WDM	The goal of ML in the field of AI is to enable the development of systems that can generalize behavior based on examples presented in an unstructured style. Inside it, in 2002, NNs were employed to predict the highest possible weekly demand based on weather conditions (water temperature, frequency, and volume of rainfall), as well as on demand levels from the previous years. The bulk of the published methodologies in the literature regarding AI applied to WDM are based on demand forecasting.	[188,189]

Considering the smart metering technology in urban areas re-engineering the water supply planning and design procedure will recognize the higher possibilities of water appliances for water saving capabilities. These studies disaggregated end-use data provided by evidence-based research showing that (1) water-efficient appliances significantly reduce peak demand; (2) smart meter data can be used to improve water service delivery infrastructure planning and design; and (3) smart meters make it possible to implement new water pricing strategies, like a TOUT. Both basic decision tree algorithms (like Trace

Wizard and Identiflow) and sensor devices installed on specific appliances that consume water and are supplemented by data mining techniques are now in use to tackle the water end use categorization challenge (e.g., Hydro Sense) [190,191]. In order to identify unique flow signature patterns for each application domain, we use a blend of pattern recognition algorithms and data mining approaches [191]. This program can keep track of when, where, and how much water is being used at any one moment. Water service providers can also benefit from this software because it provides water end-use reports of any desired property or suburb quickly.

Overall, the reviewed studies show notable progress in the application of artificial intelligence, data analytics, and the Internet of Things for intelligent demand management and water distribution. Many are currently limited to experimental or small-scale deployments, and interoperability, cybersecurity, and social behavioral constraints are not given enough thought. To translate these findings into practical frameworks, future research should focus on developing standardized data integration protocols, scalable cloud-based infrastructures, and hybrid modeling approaches that link hydraulic, environmental, and behavioral data. These advancements will make it possible for intelligent WDM systems to move from isolated technological trials to extensive, reliable, and sustainable water infrastructure.

5. Smart Agents for WDM

The incorporation of AI and the IoT into building and household water management systems represents a major technical leap in guaranteeing the economic and sustainable use of water resources. IoT makes it possible to use a network of dispersed sensors to monitor a number of factors in real time, including flow, pressure, water levels, and quality. Leak detection in real time, pump operation optimization, and improved system performance visibility are all made possible by this feature. The massive volumes of data produced by IoT devices may be processed and analyzed by AI, which can also provide automated and predictive insights. AI systems, for example, can predict water demand, identify unusual patterns of usage, and provide decision assistance to utility operators and customers. These technologies work together to increase system sustainability and responsiveness, decrease waste, and encourage more educated water use.

Nevertheless, there are significant drawbacks to using IoT and AI in actual household water management systems despite these advantages. Installing sensors, data networks, and power systems, among other IoT infrastructure, can be prohibitively expensive initially, particularly in older or low-income housing environments. Performance deteriorates with time as a result of frequent neglect of maintenance needs including sensor calibration and battery replacement. In addition, the diverse characteristics of residential infrastructure make it more difficult to integrate these technologies as current systems could not be standardized enough to support the smooth implementation of IoT. Like this, AI has the potential to improve water consumption and forecast failures, but it mostly relies on high-quality, historical data—which is usually unavailable or insufficient in real-world situations.

The problem of data security and privacy is another major worry. IoT devices are susceptible to cyberthreats such as data manipulation, illegal access, and denial-of-service attacks, especially when placed over a dispersed and frequently unprotected network, as in household settings. Without strict privacy protections, many users could be reluctant to share patterns of family behavior that are revealed by the extremely sensitive data that is gathered. Furthermore, the dangers of interoperability and system vulnerabilities are increased by the absence of standardized IoT designs and protocols. Despite its strength, AI systems have a “black box” problem that makes it hard for stakeholders to comprehend or have faith in the decision-making processes, particularly when they are utilized for crucial resource management.

Implementation strategies that are user-centric and strategic are required to fully utilize IoT and AI in smart home water systems. This entails creating scalable and modular systems that can be implemented gradually, beginning with necessary parts like leak detectors or smart meters. It will also be essential to ensure interoperability across platforms and devices and to promote open communication standards. Furthermore, integrating cloud and edge computing models may provide deep insights and real-time responsiveness while lowering latency and protecting privacy. In the end, overcoming present obstacles and accomplishing significant change in water sustainability for residential and building environments will depend on raising user awareness, providing incentives for adoption, and making sure that strong governance frameworks around data and cybersecurity are in place.

The IoT allows for the interconnection and subsequent real-time monitoring of various devices and sensors. It may be used in WDM to keep tabs on water's pressure, quality, and flow rate, as well as to spot any leaking or otherwise unusual spots. IoT sensors used in water pipes, for instance, may report on flow rates and pressure in real time, facilitating early leak identification and minimizing downtime for repairs. Water use data is collected and sent in real time using smart meters as part of an Advanced Metering Infrastructure (AMI). Accurate invoicing, leak detection, and demand control are all made possible by this technology. One of the uses of AMI in WDM is the use of smart water meters in commercial and residential properties to provide automatic meter reading and early identification of usage anomalies.

5.1. Smart City Concept

Water distribution management may be greatly aided by the use of smart city technology. Management of the water distribution system is crucial for ensuring that water reaches homes and businesses in a timely and reliable manner. However, conventional methods of water distribution management often result in waste, overuse, and leaks. There are a number of ways in which the management of water distribution may be enhanced with the use of smart city technology including sensors, data analytics, and automation.

Water flow, pressure, and quality may all be monitored in real time with the help of smart sensors dispersed throughout the distribution system. This information may be used to locate water leaks, monitor water use, and identify problem locations in the water distribution system.

Using information gathered from sensors and other sources, analysts may create models to foresee future water needs and spot problems before they escalate. Decisions concerning water supply and distribution may be better informed by this. Many tasks associated with water distribution management can be automated with the help of smart city technologies, such as cutting off water to areas with leaks or to individual properties with high water consumption. One of the examples for smart cities is Copenhagen. The Copenhagen Solutions Lab's air quality, energy use, traffic, and garbage collection monitoring system won an award in 2017. In addition to connecting parking lots, traffic signals, buildings, smart meters, and EV chargers, the system provides real-time traffic guidance. Also, the system in water distribution installed in the city provides better life to the citizens.

Smart city technology may encourage water conservation by informing residents of their water use in real time and rewarding them monetarily for using less water. Water management may benefit from smart city technology by increasing efficiency in distribution, decreasing waste and misuse, and enlisting consumer participation in water conservation. Cities may better satisfy the requirements of their inhabitants and companies by using these technologies to construct water systems that are more sustainable and resilient.

5.1.1. Smart Water Management (SWM)

SWM is the practice of managing water resources in a way that is both effective and sustainable via the integration of data analytics, AI, and cutting-edge technology. Optimizing water monitoring, distribution, and conservation requires integrating sensor networks, IoT devices, data collecting and analysis, and automation. When it comes to managing water resources, SWM systems allow for real-time monitoring and control, increase operational efficiency, decrease water loss, and improve decision-making. SWM seeks to increase water security and resilience in urban, agricultural, and industrial contexts by ensuring the efficient and sustainable use of water resources, improving water quality, and reducing environmental consequences.

Managing and optimizing water systems, especially water distribution, is an example of SWM. Utilities may cut down on wasteful water leaks and boost the longevity of their water distribution networks by adopting SWM practices. Optimizing water pressure in the distribution system is another area where SWM may aid water utilities. Utilities may increase distribution network efficiency and decrease water loss from leaks by regulating water pressure. Predictive analytics may be used by modern water management systems to anticipate future water needs and identify trouble spots. This may aid water companies in optimizing their distribution system for future demand.

The real-time monitoring of water quality made possible by SWM systems enables utilities to address any problems as soon as they develop. This may aid in ensuring that the water supplied to customers is safe and abides by all applicable regulations. Overall, SWM technology may aid water utilities in water distribution management by providing useful insights into waste reduction, efficiency enhancement, and long-term sustainability. Water utilities that adopt these technologies will be better equipped to meet the needs of their customers and improve the well-being of the communities they serve.

Several international (United States, China, India, Brazil, Australia, European Union) research programs [192–195] looked at the use of smart sensor and meter monitoring in water systems to encourage water saving. Water saving concepts were integrated into a set of decision-support tools for water utilities and consumers, applicable in varying local conditions [193,196,197], and data management and information extraction from massive amounts of higher solution consumption data were also implemented to influence behavioral change. Smart metering helped water utilities pinpoint pressure and flow issues, but they still were not able to properly solve the water-energy nexus. There are a wide variety of practical purposes for water quality monitoring, including but not limited to tracking pressure fluctuations throughout pipes, monitoring water quality in aquariums, monitoring water use in homes, and detecting chemical leakages in rivers near plants.

The higher difficulty in monitoring a network's total water use has resulted in a lower rate of deployment of Demand Response systems in the water and wastewater sectors. In the field of theoretical research on pumping activity in water systems, there are surprisingly few examples [198]. Only a Blockchain platform, which in [199] integrates renewable energy and water systems to generate efficiency, is now being used in a pilot project. To integrate smart contracts into the current platform, it tests Blockchain in conjunction with sensors that track the flow of water and serve as "gates" to validate supply to customers and release payments to utilities on their behalf. No practical outcomes have been obtained as of yet.

5.1.2. Smart Water Management at Residential Buildings

For improving water efficiency and sustainability in residential buildings, SWM has become a game-changer. In light of growing urbanization, climate change, and water shortage, conventional water systems frequently fail to detect leaks or inefficiencies in

usage. In order to track consumption in real time, identify irregularities, and improve distribution, SWM makes use of technology like AI and high-resolution smart meters. Along with lowering operating expenses and improving resource conservation, this also gives customers access to consumption data. As a result, SWM is essential to the creation of water-smart communities, the endorsement of climate adaptation strategies, and the advancement of sustainable development in the building industry.

The usefulness and practical use of SWM in residential settings have been shown in several research works. In a Northern Italian case study, researchers installed 23 smart meters in various residential structures to track water usage over a two-year period at 1-min intervals. They created an autonomous detection system that uses cumulative gradient thresholds and early morning consumption to identify days when gardens are irrigated. By differentiating between days with and without irrigation, this categorization made it possible to better analyze patterns of water usage and supported better pressure control in distribution networks [200]. According to the study, irrigation usually took place between two and five in the morning, which had a major impact on daily demand curves and provided obvious benefits for predictive management techniques.

In the meantime, [201] used end-use data from 252 households in Australia to create an ANN model that forecasts residential water demand at the appliance level, including washing machines, showers, and toilets, based on socioeconomic, demographic, and appliance efficiency factors. This model demonstrated the value of granular data in policymaking and was helpful in estimating water savings from retrofit initiatives. These examples collectively demonstrate how ML and high-resolution monitoring techniques may reveal trends in consumption, facilitate anomaly identification, and maximize both immediate operations and long-term water conservation plans.

Numerous research works and applications in Saudi Arabia show how SWM is becoming more common in household settings. Ref. [202] examined how households behaved during the COVID-19 lockdown and found that increased cleanliness, online learning, and remote work significantly increased water use. Furthermore, an SWM system suited for buildings with sporadic water supplies was created and tested by Ref. [203] in 2021. This system improved availability and energy efficiency while lowering waste by controlling water levels between rooftop and subterranean tanks using real-time sensors and automated controls. These instances demonstrate Saudi Arabia's proactive use of smart technology to improve sustainability and water efficiency in the residential sector.

The use of SWM in residential structures offers practical insights that improve conventional water management and make it more sustainable, intelligent, and flexible. Building managers and municipal planners may identify inefficiencies, encourage conservation practices, and put customized methods like leak detection, pressure optimization, and efficient appliance usage into practice by gathering and evaluating fine-scale consumption data. In the future, increased usage in a variety of residential settings, together with the integration of AI and IoT, can improve the resilience of water infrastructure. Furthermore, integrating SWM data with behavioral, economic, and climatic elements would provide holistic water governance, enhancing the building sector's contribution to international water sustainability objectives.

5.1.3. Information and Communication Technologies (ICT)

A close examination of the aforementioned methods reveals some limitations. Currently, data from smart sensors/meters is used by ICT-based service platforms to analyze and optimize water resources, but this concept has not yet been extended to include both water and energy flows in water systems. Similarly, demand response (DR) systems are not currently being considered for implementation in water systems in order to achieve energy

and water savings. They have not yet implemented a feedback loop for energy use that is associated with water use. Insufficient research was done on Blockchain and AI-based technologies for them to be ready for usage in water infrastructure. Fewer initiatives sought to build an ICT-based service platform to analyze and optimize water resources by making use of data from smart sensors and meters.

The proposed smart management platform takes into account supervisory control of both water and energy flows in order to improve water and energy efficiency, while also offering the possibility of carrying out transactions directly between utilities and local renewable producers. Information from smart meters about water and energy use is combined with data analysis (profiling, modeling, simulation, and optimization) performed with the help of AI, a disaster relief program, and services for P2P transactions between water utilities and local renewable producers using smart contracts (inside microgrids).

The software components that work together include integrated water and energy database management, which performs in-depth analyses of integrated databases to characterize various patterns at the level of water and energy pump stations and customers (water). Clustering and Kohonen networks are used in an integrated water and energy forecasting model to provide accurate predictions of future water and energy needs.

Smart management, based on process modeling and predictions of energy and water consumption, necessitates the employment of meta-heuristic mathematical optimization models and computational algorithms for the water distribution process. The ability for water pumps to take part in a DR system is increased by power consumption management, which is addressed by the DR program. The potential influence of Blockchain technology on the combined water and power sectors is examined, as are the possibilities it may provide for water utilities.

5.1.4. IoT

IoT is not a new concept; however, recent advancements in a variety of technologies have made it a viable one. Low-power, low-cost sensor technology is now available. More companies can afford to use IoT technology now that sensors are becoming more accessible and affordable.

- Connectivity: Connecting sensors to the cloud and other "things" has never been easier because of the proliferation of network protocols for the internet.
- Cloud computing systems: The proliferation of cloud platforms gives companies and individuals easy access to scalable infrastructure without the overhead of managing it themselves.
- Analytics and ML: Businesses now have easier and quicker access to valuable insights due to developments in ML and analytics, as well as the diverse and large volumes of data stored on the cloud. The data generated by IoT also fuels these ancillary technologies, whose rise continues to push the frontiers of IoT.
- AI capable of human-like conversation: IoT devices (such as digital personal assistants like Alexa, Cortana, and Siri) now have access to natural language processing (NLP) thanks to developments in neural networks.

To create mathematical models and computational algorithms based on meta-heuristic methods to optimization and expert systems for decision making in pumping water management, AI-based modeling and simulation techniques are used. When water utilities adopt the DR idea, they may achieve considerable reductions in wasteful pumping activity, which in turn saves a lot of water and energy and, ultimately, money for their customers. An IoT-based WMS includes a controller, sensors, and a data-viewing application.

There are several factors to consider when assessing drinking water quality. Certain measures of quality may be taken with nothing more than a measuring stick and some

experience, while others are more involved and need specialized instruments and personnel. The effects of water quality issues on the health of locals were investigated by measuring parameters including turbidity, temperature, total dissolved solids, conductivity, pH, chloride, sulphate, magnesium, calcium, sodium, potassium, nitrate, and bacteria. All measured values were found to be within acceptable ranges, as established by WHO standards. The examples of commonly used water quality parameters are pH, dissolved oxygen, turbidity, conductivity, total dissolved solids, temperature, and salinity.

The IoT can help mitigate some of the discerning trends. With the help of sensors, big data, and AI technologies, "smart" water monitoring and management systems can help water utility operators, farmers, and businesses track and manage the quantity and quality of water flowing through their pipes. Preserving our planet's resources can be greatly aided by reducing waste and consumption and enhancing how we manage water quality.

In order to maximize transparency and make more reasonable and sustainable use of water resources, the field of SWM has developed a suite of IoT technologies to aid in the planning, development, distribution, and management of the use of water resources. In the IoT ecosystem, a wide variety of sensors are able to measure distance, temperature, humidity, and more. Common sensors include ultrasonic, temperature, and pH sensors. Several low-power communication protocols have been developed to accommodate the many requirements of IoT devices and networks, including those that are low on power, need a large amount of memory, and are short on resources. Several wireless networking standards fall under this category, such as Bluetooth Low Energy (BLE), Zigbee, Low-Power Wi-Fi, Narrowband IoT (NB-IoT), Low Range (LoRA), and so on. In BLE, all peripheral devices remain in sleep mode until they receive a packet from the central node, at which point they immediately become active. As a result, the network's total energy usage drops. Yet Low-Power Wi-Fi, which uses the IEEE 802.11ah standard, can transmit farther than traditional Wi-Fi networks while using much less power. Zigbee is based on the IEEE 802.15.4 standard and is used in settings requiring low data rate short range communication, such as in automation, factories, and so on. Both LoRA and NB-IoT are built on LPWANs, or Low-Power Wide Area Networks. To date, LoRA is the only commercially used low-cost communication technology. There is a maximum data rate of 50 kbps; however, it allows for communication across vast distances. Nevertheless, NB-faster IoT's data throughput comes at the expense of lower consumption compared to LoRA and a higher cost per device.

5.1.5. Smart Metering

Smart meters are a cutting-edge technology that may assist streamline water distribution operations by recording consumption data in real time. Utilities can track trends of water consumption and pinpoint spots of over- or under-use by installing smart meters throughout the water distribution system. This may aid utilities in maximizing water efficiency by enhancing distribution efficiency, decreasing leakage, and minimizing waste.

By giving people access to their water use in real time, smart metering may encourage water conservation. Consumers could be encouraged to adopt more sustainable water habits if they could see how much water they were consuming and how much it was costing them. Considering more detailed data on water consumption, smart meters may also help improve the accuracy of water bills. Utility companies and their customers may have fewer disagreements and billing mistakes as a result of this. Smart meters may help utilities cut down on wasteful water use, boost productivity, and encourage conservation via their distribution systems. Utilities may better serve their customers and communities by incorporating smart metering technologies into the design of their water distribution networks.

Generally speaking, the following are the most important aspects of a smart sensor for use in environmental analysis. All measurements must be accurate, which necessitates the following components:

- Detection/transduction system to convert the analytical signal into a measurable electrical quantity.
- Suitable measurement and signal processing interface to shape the electrical signal.
- Data processing together with a calibration system to ensure the measurement is accurate.
- Autonomous power source to guarantee the nonstop operation of the entire process.

5.1.6. Demand Response (DR)

Utilities use DR to control peak power demand by offering financial incentives to customers who agree to lower their electricity consumption at such times. Yet another area where DR has proven useful is in the management of water distribution, namely, during times of excessive water consumption or water shortage. Water utilities may give incentives to customers to reduce their water consumption at peak hours, just as DR does for electricity saving. Consumers may be encouraged to limit their water use during peak demand times if financial incentives are offered [204].

Consumers may be encouraged to adjust their water use at non-peak times thanks to DR. Utilities, for instance, might incentivize customers to conduct water-intensive chores like washing clothes or watering lawns during off-peak hours by offering discounted rates. When water is scarce, DR may be used to control demand and cut down on shortages. Utilities may better manage water resources by reducing the overall demand for water and offering incentives to users to lower their water consumption. DR is also useful for encouraging water providers to upgrade to more efficient water distribution infrastructure. Utilities may minimize waste, boost distribution efficiency, and control peak demand all by adjusting water flow and pressure [205].

6. Common Barriers of Applying WDM

Many obstacles stand in the way of our ability to anticipate trends in water quality and examine the processes underlying these data resources.

Data abundance: When considering both the spatial and temporal dimensions, the data pool is often rather substantial. Yet, there are two key reasons why the overlap between two circumstances (such as the same time and same place) is usually rather minor or nonexistent in reality. To begin with, sample takers are not always adhering to protocol (leading to incomplete indicator collecting and missing data). The second reason is that the standards for data collection have evolved over the last several years (some indications may no longer be included). They cause gaps in the dataset. These kinds of problems occur often while gathering information on water quality.

Current sensor technologies provide real-time data gathering for most of the physical and chemical markers of water quality, allowing for synchronization of data. The state of our health may be measured by many biological parameters. Nevertheless, it might take anything from a few hours to a day for the tests to determine which germs are present. Thus, it is challenging to synchronize the data set's various indications due to these factors.

There are a number of challenges that must be overcome in order to establish efficient water distribution management, and they fall into one of three broad categories: social, economic, and technological.

Social Impasses: Problems with how the general public reacts, acts, and becomes involved are examples of social barriers. Those things may consist of the following:

(a) Lacking in Education and Awareness: The necessity of water conservation and effective distribution practices may not be well known in many areas due to a lack of awareness and education. Because of this, water may be used inefficiently, and distribution systems may not be properly maintained.
(b) Resistance to Change: Stakeholders may be hesitant to adopt new water distribution practices due to their comfort with the status quo. This may be a barrier to implementing new methods of administration and cutting-edge technology.
(c) Inadequate Community Engagement: The effectiveness of water distribution management plans may be hampered by a lack of active engagement and involvement from local communities, which is often the result of Inadequate Community Engagement. Sustainable water management relies heavily on public participation, education, and involvement in policymaking.

Educating populations on the value of water conservation, the efficacy of efficient distribution practices, and the advantages of better water management via the use of public awareness programs is essential. Through stakeholder engagement, communities and non-governmental organizations (NGOs) are brought into the decision-making process so that their interests and needs may be taken into account. Programs to encourage responsible water usage via incentives, restrictions, and education are being developed under the heading "Social and Behavioral Change Programs."

Challenges in the Economy: The term "economic obstacles" is used to describe the difficulties associated with implementing efficient water distribution management due to cost limits and other economic reasons. Among these challenges are the following:

Affordability: Inequitable access and distribution management may arise when people in certain areas cannot afford water services.

Cost Recovery: In places with low financial resources, it might be difficult to provide sustainable funding models and ways to recover expenses connected with water delivery.

Funding for infrastructure construction and upkeep may be attained via creative financing models including public-private partnerships, concessional funding, and cost-sharing systems. Reforming water rates such that they are equitable across socioeconomic categories and allow for full cost recovery is known as tariff reform. Water distribution systems may be made more efficient by investments in technology and infrastructure modifications, which in turn save operating costs and improve management.

Technical Barriers: These include issues with water distribution management's infrastructure, technology, and operations. Some examples of such challenges are as follows:

Aged Infrastructure: Many water distribution systems across the globe are hampered by outdated pipe, pump, and valve infrastructures. This may cause leaks, inefficiency, and expensive maintenance.

Non-Revenue Water: Water distribution management is complicated by non-revenue water, which includes losses from leaks, theft, and faulty metering. Non-revenue water may be reduced by the use of effective metering, pressure management systems, and leak detection technology.

Data Management Consideration: Accurate data collection, analysis, and monitoring are crucial for efficient water distribution management. In order to boost productivity and make better decisions, businesses need to invest in modern metering infrastructure and data analytics.

Several international strategies may be used to overcome these challenges. More effective and long-lasting water distribution may be achieved via the use of integrated water resource management strategies that take into account all aspects of the water cycle, from production through distribution to treatment of wastewater. Effectively addressing social, economic, and technical difficulties requires including a wide range of stakeholders, such as

local communities, government agencies, and water utilities, in decision-making processes. Figure 5 shows the publications covering all the factors regarding the current topic.

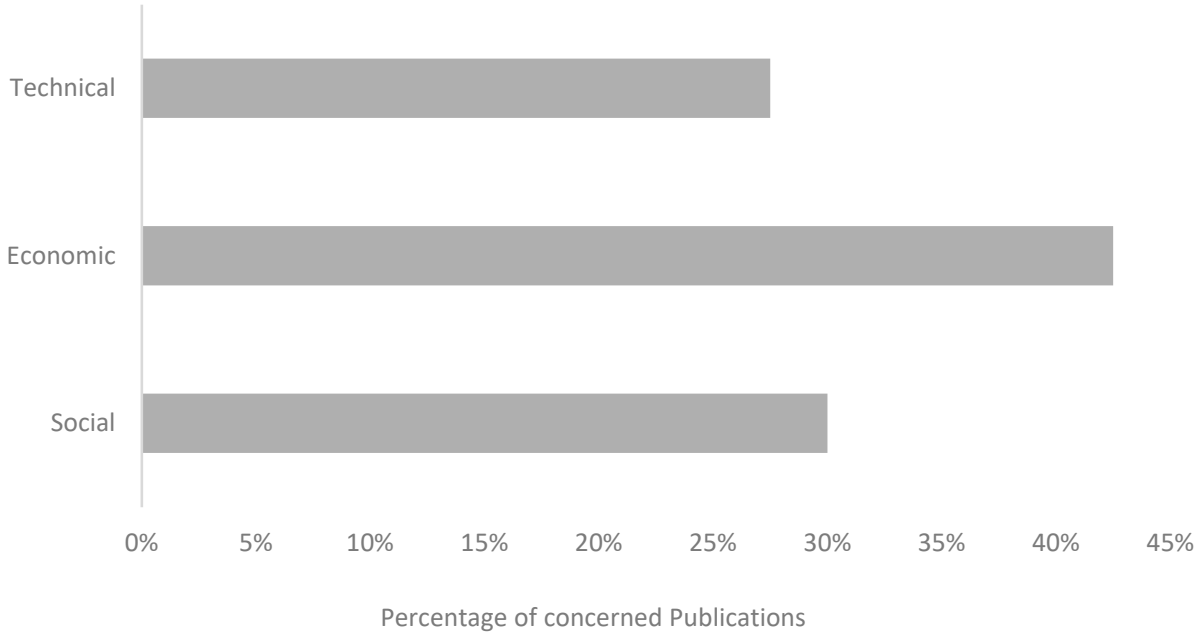


Figure 5. Percentages of concerned publications on definite topics.

Promoting projects, training programs, and information sharing platforms aimed at capacity development may increase knowledge, ability, and experience in water distribution management. Smart metering, remote sensing, and data analytics are just a few examples of the cutting-edge technologies that may be used to boost water distribution efficiency, leak detection, and policymaking.

The ultimate goal of drinking water quality regulation is to enhance health, which is why risk analysis is so important. There have been widespread epidemics caused by certain species of bacteria. They may cause permanent damage to the public water supply if they are transmitted via the system that delivers drinking water. Managing water quality risks raises important problems of timeliness and precision.

7. Conclusions

This review emphasizes the value of smart technology in enhancing Water Demand Management (WDM), particularly in residential settings. Innovations like remote sensing, real-time monitoring, advanced metering infrastructure, and predictive analytics provide practical validated solutions to reduce water waste, optimize supply, and improve responsiveness. For instance, AI-based forecasting and IoT-enabled leak detection have demonstrated water savings of up to 30% in residential networks [142,143] while smart rain-barrel coordination systems such as Smartin resulted in measurable reductions in the demand for potable water and combined sewer overflow [146].

Similarly, depending on user behavior and geographic context, household interventions like dual-flush toilets and low-flow fixtures can reduce domestic water use by 20–40% [52,53]. Notwithstanding these developments, there are still institutional, financial, and technical obstacles, particularly when it comes to scaling adoption across geographical areas with varying levels of infrastructure preparedness and policy maturity.

To accelerate the process, policymakers and public authorities should prioritize integrated digital platforms and interoperable data standards that minimize duplication and lower implementation costs. Real-time feedback loops and dynamic pricing strategies

can lower peak demand by 10–15% and improve user adherence to conservation goals, according to evidence from peer-reviewed studies [75]. Investors in mobile applications and public dashboards simultaneously raise consumer awareness and encourage long-term behavioral change [151]. Strong cybersecurity and data management must also be guaranteed by regulatory frameworks, and incentive tariffs and modern building codes can encourage the broad use of water-efficient technologies like automated consumption control, smart irrigation, and leak detection.

Future research should evaluate the cost-benefit trade-offs of different smart WDM technologies under a variety of climatic and socioeconomic conditions. Comparative studies of governance models that promote cross-sector collaboration, particularly between utilities, municipalities, and technology providers, would reveal the best durable institutional arrangements. To ensure that smart water systems remain ecologically and socially inclusive, it is also essential to research equality, customer trust, and data ethics.

There are certain criteria that need to be met to implement the proposed governance architecture. The roles and duties of water utilities, local government agencies, and technology partners should be clearly defined in order to maintain accountability and reduce functional overlap. Fostering trust, openness, and real-time information sharing among stakeholders also requires the establishment of standardized data-sharing protocols and interoperability frameworks. Furthermore, financial tools and regulatory incentives can encourage joint investments in digital innovation and infrastructure modernization, while digital literacy programs and capacity-building projects improve local agencies' institutional preparedness to take part in smart water governance. All these facilitators work together to change the governance framework from a theoretical idea into a workable system that promotes long-term cross-sector cooperation.

Finally, previous studies have shown that smart WDM systems can have measurable effects by bringing together technological innovation and concrete policy measures. These effects include a 30% reduction in household water consumption, improved network resilience and a contribution to a more sustainable and water-secure future [144].

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