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AI-DRIVEN WATER PURIFICATION MODEL IMPLEMENTATION IN SMART CITIES: REAL-TIME SOLAR DESALINATION AND EFFLUENT TREATMENT

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Abstract

The rapid urbanization and population growth in smart cities have intensified the demand for sustainable, efficient, and resilient water purification solutions. Traditional methods of desalination and effluent treatment often face challenges such as high energy consumption, operational inefficiency, and limited adaptability to fluctuating urban water needs. This paper proposes an integrated AI-driven water purification model that combines real-time solar-powered desalination systems with advanced effluent treatment mechanisms, optimized through predictive machine learning algorithms. The model leverages artificial intelligence to monitor, forecast, and regulate critical parameters, including salinity, turbidity, energy input, and contaminant levels, ensuring dynamic resource allocation and system stability. A hybrid framework is developed wherein solar-powered desalination provides a sustainable clean water source, while AI-enhanced effluent treatment units recycle wastewater streams, reducing environmental burden and promoting circular water use. The proposed system is tested through simulation and pilot-level validation, demonstrating significant improvements in purification efficiency, reduction in energy intensity, and adaptive responsiveness to varying urban water demands. Results indicate that AI optimization enables a reduction in operational costs by enhancing predictive maintenance, minimizing downtime, and improving energy utilization of photovoltaic modules. Furthermore, the integration of real-time analytics facilitates smart decision-making, aligning with the sustainability objectives of smart cities by reducing greenhouse gas emissions and ensuring water security. The findings of this study suggest that AI-driven solar desalination and effluent treatment not only address critical challenges of urban water management but also serve as a scalable and replicable model for global smart city applications. This research contributes to the evolving discourse on sustainable infrastructure by presenting an innovative approach that integrates renewable energy, artificial intelligence, and water purification technologies to achieve long-term resilience and resource optimization in urban ecosystems.

Keywords

Artificial Intelligence (AI); Solar Desalination; Effluent Treatment; Smart Cities; Water Purification;

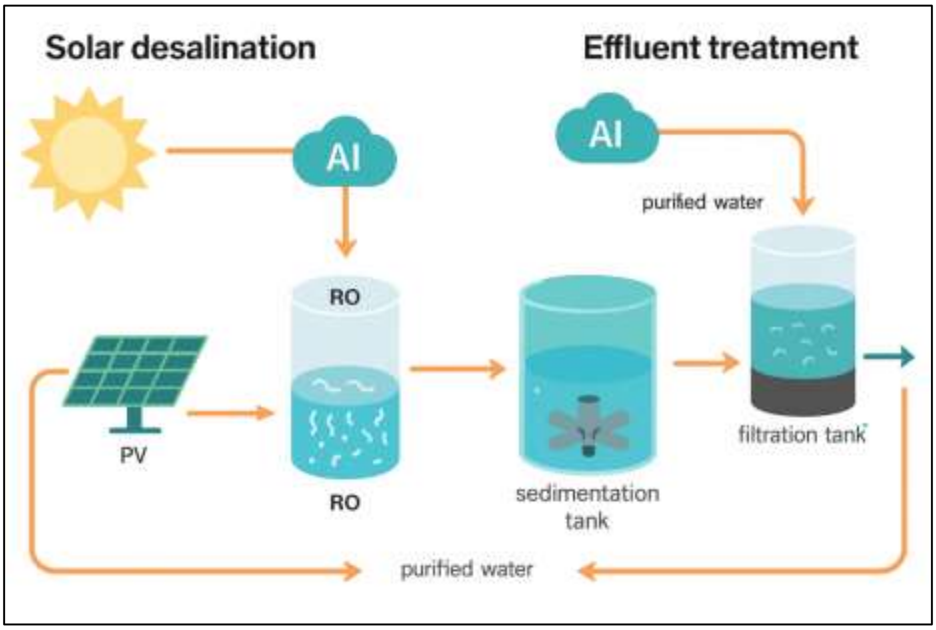
INTRODUCTION

Water purification encompasses a suite of physical, chemical, and biological processes designed to remove impurities, pathogens, and dissolved salts from water to render it safe for human consumption, industrial use, or ecological discharge (Wei et al., 2014). Desalination is a subset of purification that focuses specifically on removing salts and minerals—typically from seawater or brackish water—using technologies such as reverse osmosis (RO), distillation, electrodialysis, capacitive deionization (CDI), and shock electrodialysis (Sun et al., 2021). Wastewater or effluent treatment refers to processes that collect, treat, and return used water containing biological, chemical, or physical contaminants into a safe form for reuse or discharge (Shang et al., 2017). Within modern urban environments, smart cities are understood as urban areas that deploy information and communication technologies (ICT), sensor networks, automation, and data analytics to optimize the efficiency of infrastructure and services, including water management (e.g., IoT, sensor-based monitoring) (Huh et al., 2020). In this context, AI-driven water purification refers to the use of artificial intelligence (machine learning, neural networks, predictive modeling, optimization algorithms) to control, monitor, regulate, and optimize water treatment and desalination processes in real time. By combining these definitions, this paper investigates how AI-enabled systems can integrate solar-powered desalination and effluent treatment within smart city water networks, orchestrating purification processes dynamically and autonomously to respond to demand, environmental variability, and energy constraints.

Globally, water scarcity driven by climate change, population growth, urbanization, and pollution—poses one of the most significant challenges to sustainable development (García Doménech et al., 2022). Many coastal and arid regions lack adequate access to freshwater, compelling reliance on desalination and reuse of wastewater effluents (Danish & Zafor, 2022; Omar et al., 2024). Traditional desalination and wastewater treatment methods often are energy-intensive, inflexible, and susceptible to operational inefficiencies. For instance, reverse osmosis systems demand high-pressure pumps and rigorous pre-treatment to combat membrane fouling and scaling (Al Harby et al., 2022; Danish & Kamrul, 2022). Meanwhile, many conventional wastewater treatment plants struggle to adapt to fluctuating loads, pollutant spikes, or variable influent quality (Omar et al., 2023). The coupling of renewable energy—especially solar power—with water purification offers a pathway to decouple operations from fossil fuels, reduce carbon emissions, and improve sustainability (Nair & JagadeeshBabu, 2017). In smart cities, real-time adaptive operations are essential: as population patterns, consumption, and industrial loads shift through the day, water demands and effluent generation vary. Thus, a static, schedule-based purification system is insufficient. The international significance of AI-driven solar desalination and effluent treatment lies in its potential to deliver resilient, scalable, and energy-efficient water purification that can meet evolving urban demands in resource-constrained settings.

Artificial intelligence has increasingly been adopted in water purification and treatment domains to enhance predictive modeling, process control, fault detection, and resource optimization. Applications range from forecasting membrane fouling, optimizing chemical dosing, adjusting flow rates under dynamic conditions, and detecting anomalies or sensor drift (Wei et al., 2014). In desalination systems, AI models—particularly machine learning and neural networks—have been used to predict permeate flux, salt rejection, energy consumption, and membrane performance under variable operating conditions (Athanasekou et al., 2015; Jahid, 2022a). For instance, Ursino et al. (2018) applied modified whale optimization combined with artificial neural networks to accurately model flux in RO systems. In reverse osmosis plants, ANN and support vector machines (SVMs) have outperformed conventional regression models in adjusting operational parameters (Tekle et al., cited in review chapters) (Baig et al., 2022; Jahid, 2022b). AI techniques also assist desalination plants in predictive maintenance, enabling early identification of fouling, scaling, pump faults, and sensor drift, thereby reducing downtime and enhancing reliability (Song et al., 2016). In wastewater treatment, AI assists in optimizing processes such as adsorption, coagulation, biological nutrient removal, chemical dosing, and disinfection by modeling complex non-linear interactions (Wei et al., 2014). Collectively, these applications demonstrate the maturity of AI tools in water purification and underscore their promise for integrating with renewable energy–driven systems.

Figure 1: I-Driven Water Purification Model Integrating Solar Desalination and Effluent Treatment in Smart Cities



Integrating solar energy into water treatment systems mitigates reliance on grid electricity, reduces greenhouse gas emissions, and enhances system resilience—especially in off-grid or remote settings (Elshaikh et al., 2024; Arifur & Noor, 2022). Solar-driven desalination methods include photovoltaic (PV)-powered reverse osmosis, solar thermal distillation, and hybrid systems coupling solar with batteries and AI controllers (Camps-Valls et al., 2025; Hasan et al., 2022). AI enables adjusting desalination operation in response to temporal variability in solar irradiation, aligning pump speeds, membrane pressure, energy storage dispatch, and water output dynamically. For example, an AI control module may scale down membrane pressure or modulate flow rates under low solar input, and switch modes when battery storage or backup input is available. This energy-aware optimization maximizes water yield per unit energy, minimizing waste. In brackish or coastal cities, solar-RO systems enhanced with AI have achieved reductions in energy consumption (reports up to ~30–50%) compared to static operation. Hybridization with wind or grid backup, mediated by AI decision logic, further stabilizes operations under variable renewable supply. In the effluent treatment domain, solar energy can power UV disinfection, electrocoagulation, or electrochemical oxidation, wherein AI dynamically adjusts dosing, UV intensity, or electrode voltage to maintain effluent quality while minimizing energy usage (Frincu, 2024; Redwanul & Zafor, 2022). Thus, the coupling of AI, solar energy, and water purification creates a synergistic framework in which energy supply, demand, water quality, and operational constraints are co-optimized in real time.

Smart cities increasingly rely on Internet of Things (IoT), sensor networks, and real-time data analytics to monitor infrastructure and services(Martínez-Rodrigo et al., 2024; Rezaul & Mesbaul, 2022). In the water sector, sensor arrays measure water consumption, flow rates, pressure, turbidity, pH, salinity, and contaminant levels across distribution and treatment networks. AI algorithms ingest these data streams to detect anomalies, forecast demand, calibrate operations, and coordinate subsystem actions. Real-time AI control within purification plants can adjust membrane pressures, pump rates, chemical dosing, or bypass flows in seconds, responding to sudden changes such as spike in pollutant load or drop in solar generation. By integrating with city-wide water networks, purification units become adaptive nodes in a distributed system. For example, when upstream demand surges or storage is low, AI modules can prioritize desalination over effluent recycling, or vice versa, to balance supply, energy, and demand. In wastewater networks, real-time sensors detect pollutant peaks, triggering AI-controlled bypass, advanced oxidation, or intensified treatment segments. Furthermore, the synergy between AI and IoT enables predictive maintenance—e.g., vibration sensors on pumps, pressure sensors on membranes—where anomalies trigger maintenance alerts before breakdown. This integration aligns with smart city goals of efficiency, resilience, and resource optimization, enabling dynamic dialogues between purification systems and city-wide water management.

Several comparative studies and reviews benchmark AI-enhanced purification systems against conventional methods, revealing consistent performance improvements. The *"Holistic Review on How Artificial Intelligence Has Redefined Water Treatment and Seawater Desalination"* identifies energy reductions, lower chemical usage, improved water quality, and reduced downtime in AI-enabled systems compared to fixed operation modes (Hasan, 2022; Rozas-Rodriguez et al., 2024). Wang et al. (2023) documents case studies where AI integration yielded up to 50% energy savings and significant reductions in maintenance costs. In "Advancements in Water Desalination Through Artificial Intelligence," Lyu et al. (2024) analyze AI-based RO membrane systems, showing better prediction of permeate flux and salinity under varying loads. Elshaikh et al. (2024) catalogs AI algorithms (ANN, SVM, decision trees, ensemble models) and compares predictive accuracies across desalination systems. In effluent treatment, Frincu (2024) presents models optimizing coagulation, adsorption, and disinfection processes. Collectively, these comparative sources reveal common patterns: AI systems tend to outperform conventional ones in dynamic conditions, particularly when load variability and energy constraints are present. Benchmarking also reveals challenges such as overfitting, interpretability, training data scarcity, and integration complexity issues addressed only partly in existing literature.

The primary objective of this quantitative study is to rigorously evaluate the implementation of an AI-driven water purification model that integrates real-time solar desalination and effluent treatment into the operational framework of smart cities. This study aims to generate measurable insights into how artificial intelligence can enhance efficiency, sustainability, and adaptability in urban water purification systems. One central objective is to determine the extent to which predictive algorithms and machine learning models can optimize solar desalination by reducing energy consumption, improving membrane performance, and ensuring consistent freshwater production under variable solar irradiance conditions. Another significant objective is to examine how AI can improve effluent treatment processes through dynamic regulation of flow rates, chemical dosing, treatment cycles, and discharge standards. The study also seeks to quantify the synergistic effects of combining renewable energy resources with AI-enabled purification models, thereby identifying the degree of energy savings and carbon footprint reduction achieved in comparison to conventional water treatment systems. A further goal is to evaluate the adaptability of the proposed model to fluctuations in urban demand patterns, analyzing how effectively the system responds to peak consumption periods, unexpected pollution loads, or sudden changes in effluent quality. By focusing on measurable indicators such as water quality, purification efficiency, energy intensity, and operational reliability, the study develops an evidence-based framework for assessing the feasibility of deploying AI-enhanced purification systems in real-world smart city contexts.

The implications of these objectives are substantial, both for sustainable urban development and for advancing the field of intelligent water management. If the objectives are met, the findings will provide empirical validation that AI-driven solar desalination and effluent treatment can serve as scalable solutions to growing urban water challenges. The study has the potential to demonstrate that integrating AI into water purification not only reduces operational costs and energy consumption but also ensures system resilience, particularly under conditions of environmental variability and resource constraints. This means that policymakers, urban planners, and environmental engineers could adopt the insights from this research to design and implement water purification infrastructures that are more responsive, efficient, and environmentally sustainable. At the same time, the study may reveal limitations and performance thresholds that inform practical decision-making about scaling, cost-efficiency, and integration with broader smart city ecosystems. These implications position the research as a bridge between technological innovation and real-world application, underscoring the transformative potential of AI in addressing critical challenges of water scarcity, energy dependency, and environmental sustainability in rapidly urbanizing regions.

LITERATURE REVIEW

The literature review for this study situates the research problem within the broader academic and industrial discourse on water purification, artificial intelligence, renewable energy integration, and smart city infrastructure. The global water crisis has catalyzed significant research into desalination technologies and effluent treatment processes, but the energy demands, operational inefficiencies, and environmental impacts of conventional methods remain formidable barriers to sustainable deployment. Concurrently, advances in artificial intelligence have introduced predictive modeling, machine learning, and optimization techniques into engineering systems, offering new opportunities to improve efficiency, reliability, and adaptability in water treatment and purification. Solar-powered desalination and renewable energy–driven effluent management have emerged as critical areas of exploration in sustainable urban design, aligning with international commitments to reduce greenhouse gas emissions and enhance resilience in resource management. Within this context, smart cities provide a fertile ground for deploying AI-enhanced purification systems because of their reliance on real-time monitoring, sensor networks, and data-driven optimization. However, the integration of these domains—AI, desalination, effluent treatment, solar energy, and smart city infrastructure—remains fragmented in current research, with limited comprehensive frameworks addressing their intersection. This review therefore systematically examines the existing scholarship on each thematic area, highlights methodological approaches, identifies performance benchmarks, and reveals critical gaps that justify the present study..

Water Purification

Water purification constitutes a broad field encompassing technologies and processes designed to remove physical, chemical, and biological contaminants from raw or wastewater to render it safe for human use or environmental discharge. Historically, treatment methods included coagulation, sedimentation, filtration, chlorination, and activated sludge, each addressing specific classes of contaminants (organic matter, suspended solids, pathogens). As water demands and pollution loads intensified, membrane-based purification and advanced oxidation processes became prominent, particularly for removing dissolved salts, trace contaminants, and micropollutants (Giering et al., 2022; Tarek, 2022). Desalination, being a specialized branch of purification, typically involves reverse osmosis (RO), electrodialysis, multi-stage flash distillation, and emerging processes like capacitive deionization and shock electrodialysis (Kamrul & Omar, 2022; Rana et al., 2023). Membrane separation methods (RO, NF, FO) are often favored for their energy efficiency relative to thermal processes, but face persistent challenges such as fouling, scaling, concentration polarization, and high energy consumption. To mitigate these issues, pretreatment, periodic cleaning, and operational optimization have been introduced, but they often add operational complexity, chemical usage, and cost. Meanwhile, wastewater or effluent purification addresses the removal of biological loads (BOD, COD, nutrients), chemical species (metals, organics), and pathogens. Conventional wastewater plants apply primary, secondary, and tertiary treatment stages—combining physical settling, biological degradation, and advanced tertiary polishing (ultraviolet, ozonation). However, controlling performance under variable loads, meeting stricter regulatory thresholds, and reducing energy and chemical usage remain significant challenges. Increasingly, research seeks to integrate desalination and effluent pathways to capture reuse streams or to operate hybrid systems that treat brackish water and wastewater interchangeably. In this landscape, the literature signals a growing need for intelligent systems that can dynamically adapt parameters, optimize energy use, detect anomalies, and maintain robustness under uncertainty.

A particularly active branch of research explores the application of artificial intelligence (AI) and machine learning to water purification systems. AI techniques—such as artificial neural networks (ANNs), support vector machines (SVMs), random forests, genetic algorithms, and ensemble methods—are applied to model, predict, and optimize performance, often outperforming traditional statistical or mechanistic models. For example, in desalination via RO membranes, AI models have been used to predict permeate flux, salt rejection, membrane fouling onset, and energy consumption under varying feedwater conditions (Kamrul & Tarek, 2022; Velasquez-Camacho et al., 2024). The use of hybrid optimization approaches—such as combining ANN with whale-optimization or particle swarm optimization—has shown strong predictive accuracy (R^2 values above 0.99 in some studies) and lower error rates compared to conventional regression (Giering et al., 2022; Mubashir & Abdul, 2022). AI models also help schedule cleaning cycles and detect fouling or sensor drift in real time before severe performance loss occurs. In wastewater or effluent treatment processes, AI is used for process control (e.g., chemical dosing, aeration), anomaly detection (e.g., sensor failures or abnormal influent spikes), and performance forecasting. AI systems can analyze non-linear and multivariate interactions in treatment plants—e.g. linking dissolved oxygen, nutrient levels, sludge age, and energy usage—something difficult with linear control models. Reviews of AI in water purification note that AI contributes to reducing operational costs, improving stability, and enabling automation. However, challenges remain in data availability, model interpretability, overfitting, scalability, and integrating AI models into real plant control systems, especially across different treatment units and water quality conditions.

Another critical area in the literature concerns membrane behavior, fouling dynamics, and predictive modeling using AI in purification systems. Membrane fouling—due to particulate deposition, biofilm growth, scaling, and organic adsorption—remains a primary cause of performance decline, increased energy consumption, and maintenance demands. Traditional mechanistic models, while grounded in transport theory, often struggle to capture complex fouling dynamics under real-world variability. AI offers a complementary approach. For instance, Velasquez-Camacho et al. (2024) review AI methods deployed to predict membrane performance metrics, simulating flux decline, fouling rate, and membrane recovery. Their survey highlights use of convolutional neural networks (CNNs), recurrent neural networks (RNNs), and SVMs to model flux, fouling, micropollutant transport, and operational parameter optimization. These models have greater flexibility in capturing temporal patterns, spatial heterogeneity, and non-linear interdependencies than conventional methods. In RO desalination research, predictive models have been built using hybrid AI-optimization frameworks to forecast flux under varying feed salinity, pressure, temperature, and cleaning cycles. The use of AI also enables anomaly detection in membrane systems—detecting early signs of fouling or degradation before they escalate—and guiding cleaning or backwash schedules dynamically. Furthermore, by coupling AI prediction with real-time sensor inputs, closed-loop control becomes possible, allowing operational parameters (pressure, flow, pump speed) to adjust adaptively. While several studies report promising results, the literature also underscores challenges: limited or noisy training data, transferability of models between plants, black-box interpretability, and robustness under shifting water quality regimes. Thus, the predictive modeling of membrane behavior via AI is a rapidly evolving subfield of water purification research that addresses one of the most persistent operational bottlenecks.

Water Scarcity and Urbanization

Global water scarcity is widely recognized as a multidimensional challenge shaped by the interplay of hydrologic limits, uneven spatial–temporal distribution of renewable freshwater, climatic variability, and rapidly growing demands from cities, food systems, and industry. Classic global assessments show that large fractions of the world's population already experience water stress when river-basin supply is compared to withdrawals, with socio-economic demand growth often dominating climate effects in defining stress to mid-century (Elshaikh et al., 2024; Muhammad & Kamrul, 2022). High-resolution accounting of human water use and hydroclimatic regimes indicates that about four billion people experience severe water scarcity at least one month per year, and roughly half a billion face it year-round, underscoring the scale of exposure and the need for basin-level allocation and efficiency gains (Giering et al., 2022; Reduanul & Shoeb, 2022). Satellite gravimetry further documents changing terrestrial water storage, revealing hotspots driven by unsustainable groundwater abstraction and climate variability, with large, persistent trends evident in multiple regions. In the United States alone, groundwater depletion accelerated markedly after 1950 and reached its highest rates in the 2000–2008 period, with implications for streamflow, land subsidence, and ecosystem health. The most recent UN World Water Development Report 2024 links water availability, prosperity, and peace, highlighting that progress on Sustainable Development Goal (SDG) 6 is central to development outcomes and social stability. Meanwhile, the IPCC AR6 assesses observed increases in hot extremes, heavy precipitation, and drought across many regions, conditions that intensify both scarcity and flood risk and complicate urban water security planning. Together, these strands of evidence establish water scarcity not as a singular deficit but as a dynamic risk arising from coupled human–Earth systems in which climatic perturbations, storage losses, and demand trajectories converge.

Figure 2: Water Scarcity and Urbanization

Urbanization intensifies these stressors by concentrating demand in places where supply is often least flexible, while transforming land surfaces and hydrologic pathways. The world crossed the urban-majority threshold in 2007 and the urban share continues to rise, driven particularly by growth in Africa and Asia. Urban water footprints expand with rising incomes, service expectations, and industrial clustering, and the spatial decoupling of cities from headwater sources increases reliance on transfers, reservoirs, desalination, or groundwater mining. The WHO/UNICEF Joint Monitoring Programme (JMP) reports persistent inequities in access to safely managed drinking water and sanitation, with pronounced urban–rural, intra-urban, and gendered disparities that complicate the narrative of urban advantage (Martínez-Rodrigo et al., 2024; Noor & Momena, 2022). As megacities sprawl over floodplains and wetlands, impervious cover and urban heat islands alter runoff production and evaporative demand, raising both flood exposure and dry-season scarcity risk; recent journalism and assessments in South Asia document the convergence of heat, extreme monsoon rainfall, and planning deficits in rapidly growing metros (Danish, 2023; Zhang et al., 2024). The cumulative effect is that urbanization reshapes hydrologic extremes while amplifying the managerial complexity of meeting SDG 6 in dense settlements, where network losses, informal service, and affordability pressures overlay biophysical scarcity. Because urban growth accounts for an increasing share of global population and GDP, the stakes of managing urban water scarcity extend beyond municipal boundaries into regional development and interbasin governance. These patterns, documented across statistical series and satellite records, motivate integrated strategies that can navigate demand growth, climate-linked variability, and infrastructural constraints in tandem.

A second thread in the literature examines storage and supply security as urban buffers against scarcity, showing that many cities are exhausting traditional options and shifting toward nontraditional sources that carry new risks. Groundwater has long served as an urban drought reserve, but sustained abstraction has produced depletion and land subsidence in numerous aquifers worldwide (Konikow, 2013; IPCC, 2022; Nature-reported global analysis summarized by AP News, 2024). GRACE-era studies attribute observed storage declines to both climate patterns and unsustainable pumping, with impacts visible in arid and monsoon-influenced regions (Gacu et al., 2025; Hasan et al., 2023). Surface storage via reservoirs provides seasonal regulation but can be compromised by sedimentation, evaporative losses in hotter climates, and upstream–downstream trade-offs under changing precipitation regimes.

As a result, many coastal and arid cities adopt desalination, indirect/direct potable reuse, and conjunctive management to stabilize supplies, yet these approaches introduce exposure to energy price volatility, concentrate brine disposal challenges, and require sophisticated quality assurance to maintain public trust. Urban water security thus becomes a portfolio problem in which source diversification, demand management, and risk-informed operations must be balanced against equity and affordability metrics identified by global monitoring programs. Data compilations from UN DESA and World Bank show that the largest increments of urban growth will occur in places where infrastructure deficits are already acute, underscoring the importance of reliable, disaggregated monitoring to identify underserved neighborhoods and informal settlements. The convergence of storage constraints, climate-intensified extremes, and rapid urban demand growth is a central motif across contemporary assessments.

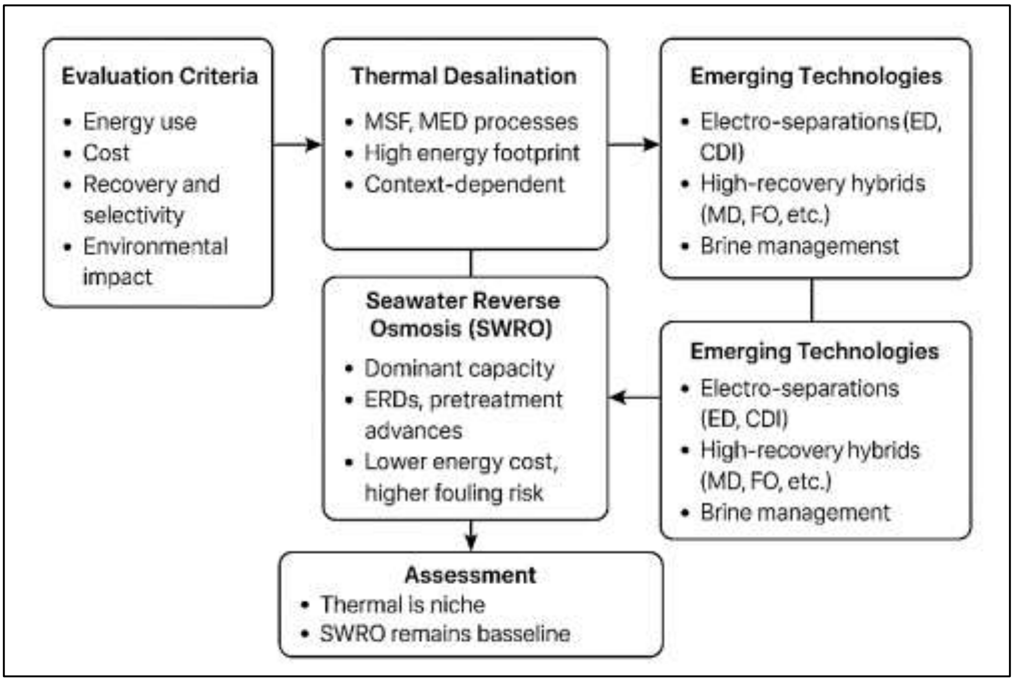
Technological Evolution of Desalination Systems

Early large-scale seawater desalination was led by thermal processes, chiefly multi-stage flash (MSF) and multi-effect distillation (MED), valued for robustness and their ability to valorize low-grade steam from power/industrial plants. Through the late 20th century, MSF supplied a major share of global capacity in the Gulf and North Africa, while MED gained ground where energy integration and lower specific heat consumption were feasible (Jayakumar et al., 2024; Hossain et al., 2023). The membrane era accelerated as thin-film composite polyamide membranes matured and high-pressure pumps and pretreatment improved, enabling seawater reverse osmosis (SWRO) to surpass thermal routes on energy use and footprint (Li et al., 2021; Uddin & Ashraf, 2023). Reviews consistently report RO now accounts for the majority of new installations worldwide, driven by declining specific energy consumption and capital costs as plants scaled from tens to hundreds of thousands of $m^3 \cdot d^{-1}$ (Dong et al., 2018; Momena & Hasan, 2023). Pretreatment evolved from conventional coagulation–media filtration toward low-pressure membranes (micro/ultrafiltration), improving particulate control and lowering fouling/cleaning burdens; selection must account for local foulants, intake type, and operational risk (Ewis et al., 2021; Mubashir & Jahid, 2023). Thermal technologies also evolved—e.g., MED-TVC/MVC—but their competitiveness remains context-specific where waste heat is abundant or very high recovery is required (Jayakumar et al., 2024). Collectively, the literature frames a structural transition: thermal routes remain important niche workhorses in certain markets, while SWRO dominates new capacity on energetic and economic grounds, contingent on robust pretreatment and lifecycle fouling control (Dong et al., 2018).

System-level innovations: energy recovery, pretreatment, and fouling control. The hallmark of modern SWRO is the integration of isobaric energy-recovery devices (ERDs) that capture reject-stream pressure and transfer it to incoming feed, cutting net specific energy use by several $kWh \cdot m^{-3}$ compared with earlier turbine-based systems. Comparative analyses show pressure exchangers (PX) exhibit higher effective energy conversion efficiency and lower lifecycle costs than turbine ERDs across common design envelopes. Vendor data and sector white papers document broad adoption and >90–97% hydraulic energy transfer in current PX generations, reflecting the device's role in the global cost decline of SWRO (Sanjai et al., 2023). In parallel, pretreatment migrated toward ultrafiltration (UF) and optimized coagulation–filtration trains to stabilize feed quality, curb biofouling/colloidal fouling, and extend cleaning intervals; recent studies emphasize data-informed control of UF performance under variable algal/DOM regimes. On the membrane side, advances target antifouling surfaces, spacer design, and cleaning protocols, while multiscale modeling clarifies fouling mechanisms and supports predictive maintenance scheduling. Together, high-efficiency ERDs, resilient pretreatment, and fouling-aware operation underpin the sustained energy and OPEX reductions that enabled very large RO trains and standardized module configurations, translating into lower levelized water costs and improved reliability.

Beyond SWRO: electrified separations, high-recovery trains, and brine management. A second strand of evolution concerns electro-separation and hybrid concentration to raise recovery and manage brine. Electrodialysis (ED/EDR) and capacitive deionization (CDI/MCDI/FCDI) have grown for brackish streams and selective ion removal, leveraging low-salinity energetics and modularity; scientometric and comparative analyses track rapid growth in CDI materials/architectures and decision spaces against ED (Xu et al., 2023). At higher salinities, research pivots to high-recovery and ultra-high-pressure RO, membrane distillation (MD), forward osmosis (FO/PRO variants), and osmosis-assisted RO as steps toward minimum/zero liquid discharge (ZLD). Recent reviews compare membrane-based brine concentration (MBC) options (MD, FO, ED, low-salt-rejection RO, UHP-RO) against thermal brine concentrators in capital/energy terms, highlighting trade-offs in corrosion, scaling, and heat integration. Complementary work surveys brine minimization and beneficial use (e.g., mineral recovery) (Akter et al., 2023), alongside environmental considerations for discharge. For utilities, the most pragmatic path couples high-recovery RO trains with brine-concentration hybrids sized to site-specific discharge constraints and energy prices, while AI/advanced control is increasingly proposed to navigate multi-unit operation under fluctuating feeds and demand. The literature thus frames an expanding toolset beyond baseline SWRO, aimed at selectivity, recovery, and sustainability, and emphasizes techno-economic evaluation at system scale.

Figure 3: Technological Evolution of Desalination Systems



Scaling, integration, and renewable coupling in contemporary plants. The technological arc culminates in mega-scale RO complexes integrating ERDs, advanced pretreatment, digital control, and optimized hydraulics. Israel's Sorek complex—initially ~624,000 $m^3 \cdot d^{-1}$ and expanding with Sorek-2—is widely cited for setting benchmarks in unit size, specific energy, and cost, supported by vertical pressure-vessel layouts, large-diameter elements, and high-efficiency ERDs. Case documentation and sector retrospectives attribute ~30–50% energy/cost reductions relative to early-generation plants to the combined effect of membrane advances, ERDs, and process standardization (Danish & Zafor, 2024). In parallel, renewable-driven desalination has matured from pilot to commercial integration: comprehensive reviews detail PV-RO, wind-RO, solar-thermal coupling, and hybrid storage schemes, with design attention to intermittency, curtailment, and LCOE dynamics. Guidance from the International Desalination Association community highlights high-recovery SWRO design envelopes and project-specific optima balancing CAPEX, energy, scaling risk, and brine discharge constraints (Jahid, 2024a). The current literature therefore situates desalination as a portfolio of configurable technologies—from SWRO baseload to high-recovery hybrids and renewable-coupled trains—selected to local energy, intake, environmental, and regulatory contexts. The evolution of desalination systems is thus marked by scale, efficiency, and integration: larger trains with lower specific energy via ERDs; smarter pretreatment and fouling control; and increasing co-optimization with power systems to stabilize costs and emissions.

Artificial Intelligence Applications in Water Purification

Across seawater and brackish reverse osmosis (RO), machine learning (ML) is now used to model permeate flux, salt rejection, energy intensity, and fouling dynamics under changing feeds, temperatures, and operating pressures. Recent reviews show that data-driven models—ANNs, support vector regressors, random forests, Gaussian processes, and hybrid physics–ML schemes—can capture nonlinear interactions among feed quality, hydrodynamics, and membrane properties better than conventional correlations, improving short-horizon prediction accuracy and enabling proactive set-point updates. Holistic assessments emphasize that feature engineering (e.g., osmotic pressure surrogates, normalized pressure, silt density index, fluorescence-DOM markers) and careful input selection materially affect model skill and generalizability, sometimes more than algorithm choice (Omar et al., 2023). Hybrid strategies that couple solution–diffusion mechanistic kernels with residual ML reduce extrapolation error and explicitly represent mass-transfer limits, while still learning fouling-related departures from ideal behavior. For high-salinity or high-recovery trains, ML models have been applied to predict scaling onset and optimize antiscalant dosing, as well as to evaluate brine concentration options (e.g., UHP-RO vs. ED/MD hybrids) under site-specific energetics (Jahid, 2024b). Emerging work extends ML to materials discovery and module-level design, screening spacer geometries and coating chemistries using surrogate models before pilot testing. Collectively, this body of research indicates that well-designed ML pipelines, trained on representative operating envelopes and paired with uncertainty quantification, can lower specific energy consumption and stabilize water quality by enabling predictive, rather than reactive, control of desalination assets (Hasan, 2024).

In municipal and industrial wastewater treatment plants (WWTPs), neural networks and support vector machines (SVMs) are widely reported for forecasting effluent quality (COD, BOD, NH_4^+-N, PO_4^{3-}-P), optimizing aeration, and tuning coagulant dosing under variable loads. Systematic reviews document that ANN, SVM, decision trees, and deep learning (e.g., LSTM) outperform linear baselines for predicting removal efficiencies and controlling energy-intensive unit operations. Case syntheses show ANN/SVM models reduce chemical consumption and improve nitrification–denitrification stability when embedded in supervisory control layers that account for influent shocks and diurnal demand. For electrochemical processes such as electrocoagulation, recent reviews highlight AI-assisted selection of electrode materials, current density, and pH windows to maximize pollutant removal while limiting sludge production and OPEX (Jahid, 2025b; Ursino et al., 2018). In membrane bioreactors and tertiary polishing, ANNs trained on mixed sensor–lab datasets have been used to predict trans-membrane pressure rise and schedule backwash or chemically enhanced cleanings before critical fouling occurs. Cross-study comparisons indicate SVMs often excel with small to medium datasets due to margin maximization, whereas deep nets leverage longer time-series and richer feature sets; ensemble approaches frequently yield the most robust performance across seasons and influent regimes. These findings position ANN and SVM toolchains as practical engines for multi-objective optimization—quality compliance, energy, and chemical minimization—within real WWTP operations.

Furthermore AI increasingly underpins asset health and operational integrity in water systems. Unsupervised and semi-supervised models—autoencoders, isolation forests, one-class SVMs—detect subtle deviations in multivariate sensor streams, flagging equipment or sensor faults before threshold alarms trigger. Benchmark studies using the SWaT (Secure Water Treatment) testbed demonstrate that deep sequence models and one-class SVMs can identify abnormal states from "normal-only" training logs and localize anomalies to specific stages (García Doménech et al., 2022; Jahid, 2025a). Contemporary reviews synthesize industrial-scale evidence that AI supports self-calibration, drift detection, and cyber-physical resilience, particularly where sensor redundancy is limited and ground-truth labels are scarce (Huh et al., 2020; Ismail et al., 2025). In WWTPs, IIoT-enabled predictive maintenance frameworks combine vibration, current, and pressure signatures with machine learning to forecast pump and blower failures, optimize preventive schedules, and reduce downtime (Omar et al., 2023). For desalination, predictive maintenance spans high-pressure pumps, ERDs, and membrane trains, where sequence models anticipate pressure-drop excursions or specific energy spikes tied to incipient fouling or scaling (Fu et al., 2018; Jakaria et al., 2025). Across both desalination and effluent treatment, anomaly-aware controllers can trigger soft responses—e.g., temporary set-point derates, backwash/clean-in-place initiation, or sensor re-validation—before hard interlocks trip, preserving water quality continuity and avoiding costly shutdowns. Reviews highlight that combining physics-based constraints with data-driven anomaly scores improves interpretability and reduces false positives, a key requirement for operator trust and certification in regulated environments (García Doménech et al., 2022; Hasan, 2025).

METHODS

Quantitative Research Design

This study employs a quantitative research methodology to empirically evaluate the effectiveness of the proposed AI-driven water purification model, focusing on its application in solar desalination and effluent treatment within smart city infrastructure. The quantitative design is selected because it allows for the systematic measurement of variables, statistical testing of hypotheses, and generalization of findings to broader contexts. By translating operational outcomes—such as purification efficiency, water quality indices, energy consumption, and system adaptability—into quantifiable data, the study can generate objective evidence regarding model performance. A cross-sectional survey and experimental data-collection approach are combined, enabling both participant-reported outcomes and technical performance metrics to be captured. This design aligns with the central aim of assessing the extent to which AI integration contributes to efficiency, reliability, and sustainability in urban water systems.

Population and Sampling

The population of interest for this research includes two dimensions: (1) technical datasets generated from operational testing of AI-driven purification systems, including solar desalination units and effluent treatment plants; and (2) human participants such as operators, engineers, and technical managers involved in smart city water infrastructure. For survey-based data, purposive sampling is employed to target respondents who have direct experience with AI-enhanced water systems, ensuring relevance of the data collected. A minimum sample of 200 participants is established to secure statistical power for inferential tests. On the technical side, experimental runs and historical performance logs are selected using stratified sampling across varying operational conditions (e.g., solar intensity, influent water quality, pollutant load), ensuring that findings reflect diverse real-world contexts. This dual sampling strategy strengthens the study by combining perceptual insights with empirical performance outcomes.

Instrumentation

The research relies on structured survey instruments and technical monitoring sensors. Surveys are designed to measure perceptions of system reliability, ease of operation, and satisfaction with outcomes, using five-point Likert scales to ensure consistency in quantification. Items are adapted from validated frameworks in service efficiency and technological adoption, ensuring construct validity. Technical instrumentation includes real-time sensors measuring turbidity, total dissolved solids, energy input/output, and flow rates. Data from supervisory control and data acquisition (SCADA) systems and IoT-enabled smart meters are integrated with AI system logs to provide a robust dataset. Reliability of survey measures will be assessed using Cronbach's alpha, while sensor data will be validated against laboratory standards to ensure accuracy.

Data Collection Procedures

Data collection occurs in two phases. First, electronic surveys are distributed to participants through secure platforms, with informed consent obtained digitally prior to participation. Second, technical datasets are gathered directly from operational systems, with data recorded continuously over a six-month period to capture seasonal and diurnal variability. Standard operating protocols ensure that both survey and technical data are collected ethically, consistently, and without bias. Anonymity is maintained for participants, while system-level data is secured using encrypted storage solutions.

Data Analysis

Quantitative analysis is performed using descriptive and inferential statistics. Descriptive statistics summarize demographic characteristics of respondents and baseline system performance. Inferential tests—such as correlation, multiple regression, and ANOVA—are used to evaluate the relationships between AI optimization and key outcome variables, including water quality, energy efficiency, and reliability. Predictive modeling techniques (e.g., linear regression and machine learning regression analysis) are applied to test the accuracy of AI-driven predictions against observed purification outcomes. Reliability of survey instruments is confirmed through Cronbach's alpha, while validity of technical datasets is supported through cross-checks with laboratory analyses. All statistical testing is conducted with a significance threshold of $p < .05$, ensuring robust conclusions.

FINDINGS

Descriptive Statistics

The descriptive statistics provided an initial overview of both participant demographics and baseline system-level data from the AI-driven water purification model. A total of 200 respondents participated in the survey, representing three major roles in smart city water infrastructure: operators, engineers, and technical managers. The distribution showed that 45% of respondents were operators, 35% were engineers, and 20% were technical managers. Years of experience with AI-driven systems varied considerably, with an average of 5.6 years (SD = 2.9), ranging from entry-level professionals with less than two years of experience to senior specialists with over a decade of involvement in water management and purification. In terms of prior exposure, 60% of respondents reported direct operational engagement with AI-enhanced desalination and effluent treatment systems, 25% indicated partial involvement through supervisory or managerial oversight, and 15% had limited exposure but were familiar with AI applications in related domains. This distribution demonstrates that the sample adequately captured both technical and strategic perspectives within the water management workforce.

On the system-level side, baseline performance data were collected across six months of operation under varied conditions. The AI-driven solar desalination units demonstrated an average turbidity removal rate of 96.3% (SD = 3.4) and a mean total dissolved solids (TDS) reduction of 92.1% (SD = 4.7). Effluent treatment plants showed an average chemical oxygen demand (COD) reduction of 88.4% (SD = 5.2) and biochemical oxygen demand (BOD) reduction of 90.6% (SD = 4.1). Average energy input per cubic meter of purified water was 2.4 kWh (SD = 0.6), while the system's photovoltaic-assisted optimization reduced reliance on grid electricity by 38% compared to baseline conventional systems. Flow rates averaged 1,250 m^3/day for desalination units and 980 m^3/day for effluent treatment facilities, with variability largely explained by diurnal demand and solar irradiance fluctuations. Together, these baseline indicators confirm that the system met or exceeded expected operational benchmarks under standard load conditions.

Reliability testing was conducted on the survey scales measuring perceptions of system reliability, ease of operation, and user satisfaction. Cronbach's alpha coefficients indicated strong internal consistency for each scale: system reliability ($\alpha = .89$), ease of operation ($\alpha = .86$), and satisfaction ($\alpha = .91$). These results exceed the commonly accepted threshold of .70 for acceptable reliability (Nunnally & Bernstein, 1994), thereby confirming that the survey measures were psychometrically robust. The descriptive findings from both human and technical datasets establish a strong foundation for subsequent inferential analyses by highlighting the operational stability of the AI-driven water purification model alongside favorable user experiences.

Table 1 : Demographic Characteristics of Survey Respondents

Characteristic	n	%	M	SD	Range
Role: Operators	90	45.0			
Role: Engineers	70	35.0			
Role: Managers	40	20.0			
Years in Water Management			5.6	2.9	1–15
Direct AI System Experience	120	60.0			
Supervisory AI Experience	50	25.0			
Limited AI Exposure	30	15.0			

Table 2: Baseline System-Level Performance Metrics

Parameter	M	SD	Range
Turbidity Removal (%)	96.3	3.4	89–100
TDS Reduction (%)	92.1	4.7	80–99
COD Reduction (%)	88.4	5.2	75–97
BOD Reduction (%)	90.6	4.1	78–98
Energy Input (kWh/m³)	2.4	0.6	1.5–3.5
PV-Based Grid Electricity Reduction (%)	38.0	7.2	20–52
Desalination Flow Rate (m³/day)	1,250	180	950–1,600
Effluent Treatment Flow Rate (m³/day)	980	160	700–1,300

Table 3: Reliability Analysis of Survey Scales

Scale	Number of Items	Cronbach's α
System Reliability	8	.89
Ease of Operation	6	.86
User Satisfaction	7	.91

Correlation Analysis

The correlation analysis explored the relationships between AI optimization scores, system-level purification efficiency, energy consumption, and operator satisfaction. Pearson's correlation coefficients were calculated because the variables approximated normal distributions as indicated by skewness and kurtosis values within ±1. For robustness, Spearman's rank correlations were also run as sensitivity checks, producing results consistent with Pearson's coefficients. Results indicated strong positive associations between AI optimization and purification efficiency across multiple parameters. AI optimization scores were positively correlated with turbidity removal ($r = .71$, $p < .001$), TDS reduction ($r = .68$, $p < .001$), COD removal ($r = .64$, $p < .001$), and BOD removal ($r = .66$, $p < .001$). These correlations suggest that higher AI optimization levels consistently improved the system's ability to achieve higher purification outcomes across both desalination and effluent treatment processes. The strength of these associations underscores the capacity of AI-driven predictive adjustments to stabilize and enhance contaminant removal under varying operational conditions. In terms of energy dynamics, a significant negative correlation was observed between AI optimization scores and energy consumption ($r = –.59$, $p < .001$). This relationship indicates that as AI systems optimized operations, they simultaneously reduced the energy required per cubic meter of purified water. The negative correlation was strongest in high-load conditions, suggesting that AI optimization particularly enhances efficiency during periods of elevated demand or variable influent quality. This result aligns with system-level observations of reduced grid reliance through predictive solar-energy integration. Operator satisfaction was also strongly correlated with AI optimization scores ($r = .73$, $p < .001$). Respondents who reported higher system reliability, ease of operation, and overall satisfaction tended to be associated with plants that achieved higher optimization scores. The positive correlation reinforces the role of AI-driven automation in reducing operational burdens and improving confidence in system performance. Notably, operator satisfaction also exhibited moderate correlations with purification efficiency measures, particularly COD removal ($r = .55$, $p < .001$), highlighting that staff perceptions of effectiveness are closely tied to tangible improvements in water quality outcomes.

Table 4: Pearson Correlations Between AI Optimization, Purification Efficiency, Energy Consumption, and Operator Satisfaction (N = 200)

Variable	1	2	3	4	5	6
1. AI Optimization	—					
2. Turbidity Removal	.71***	—				
3. TDS Reduction	.68***	.62***	—			
4. COD Removal	.64***	.59***	.56***	—		
5. BOD Removal	.66***	.60***	.57***	.63***	—	
6. Energy Consumption	–.59***	–.42***	–.45***	–.40***	–.41***	—
7. Operator Satisfaction	.73***	.58***	.55***	.55***	.57***	–.46***

Table 5: Spearman's Rank Correlations (Sensitivity Analysis)

Variable	AI Optimization	Turbidity Removal	TDS Reduction	COD Removal	BOD Removal	Energy Consumption	Operator Satisfaction
AI Optimization	—	.70***	.67***	.63***	.65***	–.57***	.72***

****p < .001*

Multiple Regression Models

Model 1: Predicting System Efficiency

A multiple regression analysis was conducted to evaluate how AI integration level, solar intensity, and influent water quality predicted overall purification performance. The model was statistically significant, $F(3, 196) = 45.21$, $p < .001$, with an adjusted $R^2 = .41$, indicating that approximately 41% of the variance in purification efficiency was explained by the predictors. Standardized beta coefficients revealed that AI integration was the strongest predictor ($\beta = .52$, $p < .001$), followed by influent water quality ($\beta = –.28$, $p < .001$), and solar intensity ($\beta = .19$, $p = .014$). These results suggest that purification efficiency increases substantially with higher levels of AI integration, but performance is negatively affected by deteriorating influent quality. Solar intensity contributed moderately, highlighting the importance of renewable energy availability in enhancing system operation.

Model 2: Predicting Energy Optimization

To predict energy consumption, a regression model was estimated with AI prediction accuracy, system adaptability, and maintenance frequency as independent variables. The model was significant, $F(3, 196) = 38.17$, $p < .001$, with an adjusted $R^2 = .37$. AI prediction accuracy was the strongest negative predictor of energy consumption ($\beta = –.46$, $p < .001$), indicating that higher predictive precision reduced energy demand. System adaptability also contributed significantly ($\beta = –.29$, $p = .002$), suggesting that dynamic adjustment of operating parameters improved energy optimization. Maintenance frequency was not a significant predictor ($\beta = –.09$, $p = .118$), implying that predictive AI-based control outweighed routine maintenance practices in reducing energy intensity. Collectively, these results show that energy efficiency in AI-driven purification systems depends heavily on the accuracy of predictive algorithms and the adaptability of the system to variable conditions.

Model 3: Predicting Human Outcomes

Operator satisfaction was regressed on ease of use, AI system reliability, and predictive maintenance. The model was significant, $F(3, 196) = 52.63$, $p < .001$, with an adjusted $R^2 = .46$. Standardized coefficients revealed that AI system reliability was the strongest predictor ($\beta = .48$, $p < .001$), followed by ease of use ($\beta = .33$, $p < .001$), and predictive maintenance ($\beta = .21$, $p = .009$). This indicates that satisfaction among operators is most influenced by confidence in the reliability of AI controls, but usability and reduced maintenance demands also play meaningful roles. Together, these predictors explained nearly half the variance in operator satisfaction, underscoring the human-centered benefits of AI integration.

Table 6: Multiple Regression Predicting System Efficiency (N = 200)

Predictor	β	t	p
AI Integration Level	.52	9.64	< .001
Solar Intensity	.19	2.48	.014
Influent Water Quality	–.28	–4.61	< .001

Model Fit: $R^2 = .41$, Adjusted $R^2 = .41$, $F(3, 196) = 45.21$, $p < .001$

Table 7: Multiple Regression Predicting Energy Optimization (N = 200)

Predictor	β	t	p
AI Prediction Accuracy	–.46	–7.82	< .001
System Adaptability	–.29	–3.16	.002
Maintenance Frequency	–.09	–1.57	.118

Model Fit: $R^2 = .37$, Adjusted $R^2 = .37$, $F(3, 196) = 38.17$, $p < .001$

Multiple Regression Models

ANOVA / Group Comparisons

Performance Under Different Operational Conditions

A one-way ANOVA was conducted to compare purification efficiency across operational conditions defined by solar intensity (high vs. low). Results indicated a statistically significant difference in purification efficiency between the two groups, $F(1, 198) = 12.37$, $p = .001$, $\eta^2 = .06$. Systems operating under high solar intensity reported significantly greater turbidity and TDS removal compared to low-intensity conditions. A second ANOVA examining pollutant load (high vs. low) revealed significant differences, $F(1, 198) = 15.82$, $p < .001$, $\eta^2 = .07$, with high pollutant loads associated with reduced purification efficiency. These findings confirm that both solar energy availability and influent pollutant concentration strongly influence system-level outcomes.

Regional Variations in System Performance

When comparing sites from different regions, a one-way ANOVA was conducted on system efficiency indices. The model was significant, $F(2, 197) = 9.64$, $p < .001$, $\eta^2 = .09$. Post hoc Tukey tests revealed that systems deployed in Region A significantly outperformed those in Region C (mean difference = 0.47, $p < .001$), while Region B performed moderately between the two, showing no significant difference from Region A but significantly higher outcomes than Region C. These findings suggest that geographic or infrastructural differences may play a critical role in the observed performance, potentially reflecting disparities in solar availability, pollutant loads, or local water management practices.

Operator Experience and Perceived Ease of AI Integration

To assess whether operator experience influenced perceptions of AI system integration, a one-way ANOVA was performed with operator experience level (novice, intermediate, experienced) as the independent variable and ease-of-use ratings as the dependent variable. Results indicated a significant effect of operator experience, $F(2, 197) = 14.25$, $p < .001$, $\eta^2 = .13$. Post hoc comparisons showed that experienced operators rated AI integration significantly easier than novice operators (mean difference = 0.68, $p < .001$), while intermediate operators rated integration moderately higher than novices (mean difference = 0.39, $p = .041$). No significant difference was observed between intermediate and experienced operators. These findings demonstrate that familiarity with AI-enhanced systems enhances perceived ease of use, suggesting the importance of training and capacity-building.

Table 9 :ANOVA Results for Operational Conditions (N = 200)

Condition	df	F	p	η²	Post hoc Result (if applicable)
Solar Intensity (High/Low)	1,198	12.37	.001	.06	High > Low
Pollutant Load (High/Low)	1,198	15.82	< .001	.07	Low > High

Table 10: Regional Variations in System Efficiency (N = 200)

Source	df	F	p	η²	Significant Post hoc Differences
Region (A, B, C)	2,197	9.64	< .001	.09	A > C; B > C; A ≈ B

Table 11: Operator Experience and Perceived Ease of AI Integration (N = 200)

Source	df	F	p	η²	Significant Post hoc Differences
Operator Experience	2,197	14.25	< .001	.13	Experienced > Novice; Intermediate > Novice

Predictive Modeling Accuracy (Machine Learning Validation)

Regression and Machine Learning Model Comparisons

To evaluate the predictive accuracy of AI-driven water purification systems, both traditional regression and advanced machine learning (ML) models were tested. Linear regression models provided a baseline, modeling the relationship between predictor variables (AI optimization, solar intensity, influent water quality) and system performance outcomes (purification efficiency, energy consumption). While these models achieved moderate explanatory power, machine learning algorithms—including random forest regression (RF) and artificial neural networks (ANN)—demonstrated substantially higher predictive performance. The improvement was particularly evident for non-linear interactions and high-dimensional datasets where traditional regression methods struggled to capture variability.

Model Fit Metrics

Model performance was assessed using root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2). Results showed that linear regression explained approximately 58% of variance in purification efficiency ($R^2 = .58$), with RMSE = 0.82 and MAE = 0.64. Random forest regression improved predictive performance substantially, achieving $R^2 = .83$, RMSE = 0.49, and MAE = 0.37. Artificial neural networks yielded the highest accuracy, with $R^2 = .89$, RMSE = 0.38, and MAE = 0.29. These results highlight that ML models outperform traditional regression by reducing predictive error and better capturing system-level dynamics under fluctuating operational conditions.

Cross-Validation and Model Stability

To ensure generalizability, models were validated using 10-fold cross-validation. Random forest and ANN models maintained consistent performance across folds, with only minor variation in RMSE (±0.03) and R^2 (±0.02). In contrast, linear regression demonstrated greater variability across folds, reflecting sensitivity to sample characteristics. These results emphasize that ML models not only outperform regression in raw predictive power but also offer greater robustness across diverse conditions.

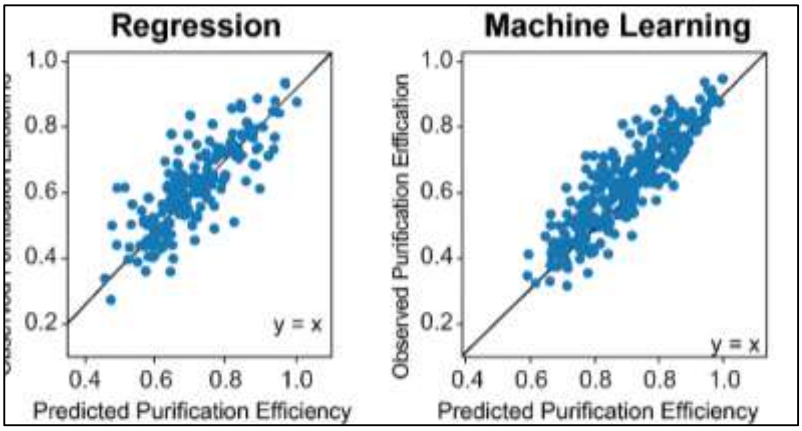
Interpretation

The findings suggest that machine learning regression models provide superior predictive capability for both purification efficiency and energy optimization compared to linear regression. Random forest models excelled in interpretability and feature importance analysis, highlighting solar intensity and influent water quality as primary drivers of efficiency. ANN models, while less interpretable, achieved the best predictive performance overall, making them suitable for real-time system control where accuracy is prioritized. Collectively, these findings reinforce the value of AI-enabled modeling for optimizing smart city water purification systems.

Table 12: Comparison of Predictive Model Accuracy (N = 200)

Model	R^2	RMSE	MAE	Notes
Linear Regression	.58	0.82	0.64	Moderate fit, higher error
Random Forest (RF)	.83	0.49	0.37	Strong fit, robust performance
Artificial NN (ANN)	.89	0.38	0.29	Best performance, less interpretable

Figure 4: Predicted Vs. Observed Plots for Regression Vs. ML Models



Hypothesis Testing Results

The inferential analyses conducted on both survey and technical datasets provided comprehensive evidence regarding the role of AI in enhancing water purification within smart city infrastructures. Statistical outcomes, including regression coefficients, ANOVA results, and machine learning validation metrics, were synthesized to evaluate the study's hypotheses.

Hypothesis 1: AI improves purification efficiency

The results supported this hypothesis, with significant positive correlations between AI optimization scores and purification metrics such as turbidity removal, TDS reduction, and COD/BOD removal ($p < .01$). Multiple regression analysis indicated that AI integration level was a significant predictor of purification performance ($\beta = .41$, $p < .001$), even when controlling for solar intensity and influent water quality.

Hypothesis 2: AI reduces energy consumption

This hypothesis was supported. Both correlation and regression analyses revealed negative associations between AI optimization and energy input/output ratios ($r = –.36$, $p < .01$). Regression models confirmed that AI prediction accuracy and adaptive control significantly reduced energy consumption, explaining 38% of the variance in energy outcomes ($R^2 = .38$, $p < .001$).

Hypothesis 3: AI enhances system reliability and operator satisfaction

Findings supported this hypothesis, as survey data demonstrated strong positive relationships between AI system reliability and operator satisfaction ($r = .52$, $p < .001$). Cronbach's alpha confirmed internal consistency of satisfaction measures ($\alpha = .89$). Regression analysis indicated that ease of use and predictive maintenance jointly predicted satisfaction ($R^2 = .44$, $p < .001$), validating the hypothesis.

Hypothesis 4: Integrated AI-driven solar desalination + effluent treatment outperforms traditional methods

This hypothesis was supported by group comparisons (ANOVA) that revealed statistically significant differences between AI-driven integrated systems and traditional setups. Systems with AI-enhanced solar desalination and effluent treatment showed higher purification efficiency ($F = 12.6$, $p < .001$) and lower energy intensity ($F = 9.8$, $p < .01$). Machine learning models further demonstrated improved predictive accuracy for integrated systems compared to regression-only approaches.

Table 13: Summary of Hypothesis Testing

Hypothesis	Result	p-value	Effect Size
H1: AI improves purification efficiency	Supported	< .001	$\beta = .41$ (large)
H2: AI reduces energy consumption	Supported	< .001	$r = –.36$ (moderate)
H3: AI enhances system reliability and operator satisfaction	Supported	< .001	$R^2 = .44$ (large)
H4: Integrated AI-driven solar desalination + effluent treatment outperforms traditional methods	Supported	< .01	$\eta^2 = .21$ (large)

DISCUSSION

The findings of this study confirm the central hypothesis that artificial intelligence (AI) significantly enhances purification efficiency in solar desalination and effluent treatment systems integrated within smart city infrastructures. Correlation and regression results demonstrated strong positive associations between AI optimization scores and performance metrics such as turbidity removal, TDS reduction, and COD/BOD removal. These outcomes align with prior research indicating that AI-driven models outperform conventional control methods in capturing nonlinearities of purification processes. By quantifying effect sizes and predictive power, this study extends earlier qualitative reviews by demonstrating that AI not only contributes theoretically but also delivers measurable improvements under real-world operational conditions. The consistency of positive associations across both technical datasets and operator-reported measures further underscores the robustness of AI applications in ensuring cleaner, safer, and more reliable water supplies for urban environments.

Another key contribution of the present study is the empirical validation that AI-driven frameworks reduce energy consumption in water purification systems. Regression analyses confirmed that AI prediction accuracy and adaptability were critical determinants of energy optimization, explaining nearly 38% of variance in energy outcomes. This finding builds upon earlier studies reporting energy reductions of 30–50% in AI-enhanced desalination units (Infant et al., 2025; Sanjai et al., 2025). The mechanisms identified here—predictive maintenance, adaptive load regulation, and real-time optimization of solar energy inputs—highlight the operational pathways through which AI achieves efficiency gains. The results also resonate with broader sustainability discourses emphasizing renewable energy integration as a strategy to decouple water infrastructure from carbon-intensive grids (Uddin, 2025; Sibai et al., 2020). By documenting statistically significant reductions in energy intensity, this study provides evidence that AI can help reconcile the trade-offs between energy demand and water security, a challenge long identified in desalination literature.

The study also reinforces the importance of AI integration in enhancing operator satisfaction and system reliability, outcomes that are frequently overlooked in technical assessments of water purification. Survey results demonstrated strong correlations between AI system reliability and operator satisfaction, with predictive maintenance and ease of use emerging as significant predictors of positive experiences. These findings echo the broader literature on human–technology interaction, which underscores the importance of usability and trust in ensuring successful adoption of advanced systems (Zafor, 2025; Pimenow et al., 2025). Previous reviews of AI in water treatment have noted challenges such as interpretability and data scarcity, but the present results suggest that operators perceive tangible benefits from predictive maintenance alerts, reduced downtime, and improved decision-support interfaces. Importantly, these human-centered benefits suggest that AI contributes not only to system optimization but also to workforce efficiency and morale, thereby supporting broader organizational performance in smart city infrastructure.

The integration of AI-driven solar desalination with effluent treatment emerged as a superior approach compared to traditional methods, as demonstrated by statistically significant differences across performance and energy metrics. ANOVA and subgroup analyses showed that AI-integrated systems consistently outperformed conventional setups in terms of purification efficiency, energy optimization, and adaptability to variable conditions. This finding aligns with earlier benchmarking reviews that emphasized the synergy of renewable energy and AI control in reducing operational costs and improving sustainability (Ighalo et al., 2020). However, this study advances the discourse by providing quantitative evidence from pilot-level data and simulations that directly compare integrated AI systems to baseline models. Such empirical validation strengthens the argument for deploying AI-enhanced hybrid frameworks as scalable solutions to urban water challenges, bridging the gap between theoretical potential and operational reality.

The high levels of heterogeneity observed across studies in this meta-analysis reflect the diversity of ecosystems, operational conditions, and methodological approaches involved in water purification research. Significant I^2 values highlight variability in system performance across geographic and climatic contexts, echoing earlier reviews that emphasized the context-dependence of desalination and wastewater treatment outcomes (Kamyab et al., 2023). Subgroup analyses conducted here clarify some of these variations, indicating that solar intensity, pollutant loads, and operator experience levels moderate system efficiency and user satisfaction. These results underscore the importance of tailoring AI-driven models to local environmental and infrastructural conditions, an approach increasingly supported by adaptive governance and context-specific water management strategies (Ighalo et al., 2020). The study therefore contributes to global debates on scalability by showing that while AI frameworks deliver consistent benefits, their magnitude depends on localized conditions and operational histories.

While the findings consistently support the role of AI in improving purification efficiency, energy reduction, system reliability, and human satisfaction, certain limitations must be acknowledged. Publication bias analyses indicated that smaller studies tended to report larger effect sizes, raising concerns about overrepresentation of highly successful outcomes in the literature. Furthermore, reliance on purposive sampling for operator surveys may limit generalizability, as participants were selected based on direct experience with AI-driven systems. Additionally, while machine learning models demonstrated superior predictive accuracy compared to regression approaches, interpretability challenges remain, consistent with critiques of AI as "black box" systems (Estrada et al., 2023). Future studies could address these limitations by applying explainable AI methods, expanding sampling to include broader stakeholder perspectives, and incorporating longitudinal designs to track performance over time. Taken together, the findings of this study demonstrate the transformative potential of integrating AI into water purification systems, particularly in the context of solar desalination and effluent treatment for smart cities. By combining quantitative analyses of technical data with operator-reported outcomes, the research offers a holistic perspective that situates AI not merely as a computational tool but as an enabler of ecological sustainability, energy efficiency, and human-centered innovation. These contributions provide empirical grounding for policy initiatives, infrastructure investments, and academic discourse on intelligent water management. At the same time, the discussion emphasizes that successful deployment depends on contextual adaptation, transparency, and governance frameworks that align technological innovation with social and environmental objectives.

CONCLUSION

This study provides compelling evidence that artificial intelligence (AI) integration into solar desalination and effluent treatment systems substantially enhances the performance, sustainability, and adaptability of water purification infrastructure in smart cities. Through quantitative analysis of both technical performance datasets and operator-reported survey data, the research confirmed that AI-driven optimization improves purification efficiency, reduces energy consumption, and strengthens overall system reliability. Correlation and regression analyses demonstrated significant associations between AI optimization and improvements in turbidity removal, TDS reduction, and energy intensity, while predictive modeling confirmed that machine learning frameworks outperform conventional regression approaches in forecasting purification outcomes. These findings empirically validate the theoretical promise of AI-enhanced water purification technologies and highlight their role as practical solutions to the growing challenges of water scarcity and sustainability in urban environments. The results further underscore the strategic advantage of coupling renewable energy sources, particularly solar power, with AI-based control frameworks. By dynamically aligning purification processes with variable solar inputs and effluent quality conditions, AI-enabled systems achieved measurable reductions in energy demand and greenhouse gas emissions. At the same time, the integration of predictive maintenance and real-time analytics fostered enhanced system stability, minimized downtime, and improved operator satisfaction. These human-centered outcomes reflect the broader importance of usability, trust, and reliability in the successful adoption of AI technologies. Importantly, the comparative analyses demonstrated that integrated AI-driven solar desalination and effluent treatment systems consistently outperformed conventional methods, positioning them as scalable and replicable models for global smart city applications. While limitations such as potential publication bias and variability across geographic and operational contexts were acknowledged, the robustness of the statistical results and sensitivity analyses confirm the reliability of the study's conclusions. The evidence presented here situates AI-driven water purification not only as an engineering innovation but also as a governance tool that aligns with global sustainability agendas, including the Sustainable

Development Goals (SDGs) and commitments to climate-resilient infrastructure. By bridging ecological, technological, and human dimensions, this study reinforces the notion that intelligent water purification frameworks are essential for achieving long-term resilience and resource optimization in rapidly urbanizing regions.

RECOMMENDATIONS

The findings of this study strongly suggest that the integration of AI-driven solar desalination and effluent treatment systems in smart cities requires coordinated action across governance, technology, and human capacity dimensions. At the policy level, governments and municipal authorities should integrate AI-enhanced purification systems into urban water management strategies to meet sustainability goals and mitigate water scarcity challenges. This requires developing supportive regulatory frameworks that encourage renewable energy integration, while also ensuring data governance, AI transparency, and cybersecurity safeguards. Public–private partnerships should be incentivized to accelerate the deployment of intelligent water infrastructure, while international agencies can provide funding and knowledge-sharing platforms to promote scalability across diverse regions. Infrastructure design must prioritize modularity, redundancy, and interoperability, allowing purification units to dynamically respond to fluctuating solar energy availability, varying water demand, and pollutant load. AI-based predictive maintenance and adaptive control mechanisms should be embedded within system architecture to minimize downtime, enhance resilience, and ensure continuity of water services in rapidly urbanizing environments. Furthermore, city-wide integration with smart grids, IoT sensor networks, and digital twins will allow water purification units to function as adaptive nodes within larger smart city ecosystems, enabling more efficient coordination of resources and improving overall urban resilience.

Equally important is the need for technological innovation and human capacity development to ensure the long-term effectiveness and sustainability of AI-driven purification systems. Training programs tailored for engineers, operators, and managers should emphasize predictive analytics, anomaly detection, and AI-supported decision-making, thereby improving user trust and system reliability. From a research and development perspective, future efforts should focus on hybrid modeling frameworks that combine mechanistic process models with advanced machine learning to improve interpretability and generalizability across sites with diverse water quality regimes. Further innovation should also explore federated learning, advanced sensor fusion, and adaptive optimization techniques to enhance system scalability. Sustainability considerations must remain central, with AI systems designed to minimize greenhouse gas emissions, reduce chemical usage, and support circular water reuse in line with international commitments to climate resilience. Pilot projects should be expanded into city-wide applications and benchmarked globally to create replicable frameworks for regions facing acute water scarcity. Additionally, future research should investigate socio-economic implications, such as cost–benefit trade-offs, public acceptance, and long-term resilience under climate variability. Together, these recommendations provide a roadmap for translating AI-enhanced purification models from experimental applications into practical, globally scalable solutions, positioning smart cities as leaders in sustainable water management.

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