Management Analytics and Social Insights

www.masi.reapress.com

Manag. Anal. Soc. Insights. Vol. 1, No. 2 (2024) 212–222.

Paper Type: Original Article

Conceptual Construction of a Water Resource Recovery and Purification System Based on an Artificial Intelligence Management Model

Hung-Li Chang[1],*, Ching-Jui Keng[1], Yu-Lun Liu[2], Han-Ling Jiang[1]

[1] College of Management, National Taipei University of Technology, Taiwan; t108749014@ntut.edu.tw, cjkeng@ntut.edu.tw; t111749016@ntut.edu.tw.

[2] Kent Business School, University of Kent, United Kingdom; y.l.liu@kent.ac.uk.

Citation:

Received: 16 Frbruary 2024 *Revised: 18 May 2024* *Accepted:18 August 2024*	Chang, H. L., Keng, Ch. J., Liu, Y. L., & Jiang, H. L. (2024). Conceptual construction of a water resource recovery and purification system based on an artificial intelligence management model. *Management analytics and social insights*, *1*(2), 212-222.

Abstract

Given the trends of energy shortages, sustainability demands, and increased awareness, along with operational challenges in water utilities, there are new opportunities for the future of water treatment. Unfortunately, current wastewater treatment systems and technologies lack integration and a comprehensive management model. This conceptual paper proposes planning and implementing a wastewater treatment system designed to enhance efficiency and reduce operating costs. It emphasizes proactive measures to ensure stable operation and aims to achieve intelligent management of wastewater treatment, guiding the industry towards more efficient and environmentally friendly practices.

Keywords: Wastewater treatment systems, Artificial intelligence, Smart water treatment system.

1 | Introduction

Extreme weather has led to a sharp increase in the frequency of global water and drought disasters, highlighting the issue of global water resource allocation [1]. According to the Global Water Intelligence research [2], the freshwater resources needed for daily drinking water, industrial development, and agricultural use will face serious shortages in the near future due to population growth and the trend of modern megacity development. Effectively applying water resources and properly treating wastewater have become urgent issues for countries worldwide.

Corresponding Author: t108749014@ntut.edu.tw

https://doi.org/10.22105/444vr378

In view of this, countries around the world are investing in the development of recycling and purification technologies for water resources to enable the reuse of one drop of water at least twice. Water reuse involves the reuse of industrial wastewater, domestic sewage, rainwater collection, agricultural irrigation return water, and seawater. In the past, wastewater treatment technologies mainly focused on removing pollutants in the water and ensuring that the treated water met the effluent standards set by the Environmental Protection Agency, often neglecting the potential for water resource reuse. However, with the increasing scarcity of global water resources, the reuse of water resources has become more important. Effectively utilizing recycled water involves encouraging various industries to adopt water recycling technologies, particularly in agricultural irrigation, industrial processes, and landscape irrigation. This approach helps alleviate the pressure on natural water resources and promotes sustainable water resource development [3–5].

Leveraging technology to address water resource shortages has become one of the most important issues of the 21st century. In 2009, IBM proposed the concept of a "smart water supply network" aimed at achieving efficient water supply through Information and Communications Technology (ICT) [5], [6]. Today, countries such as the United States, China, Australia, Israel, and South Korea, and international companies like IBM, GE, Hitachi, and Schneider have all initiated related plans or projects. Although the specific content of the smart water supply network varies among different parties, the main goal is to use technology to help solve the problem of water resource shortages and apply it widely in daily life with automated control and water resources. Water quality monitoring equipment in various countries is moving towards automation, intelligence, and miniaturization. The application market for water quality monitoring equipment is broad, including tap water, municipal/industrial wastewater treatment, industrial water treatment and discharge, river and marine environmental pollution monitoring, achieving early warning, effective resource management, regulatory compliance monitoring, improving production efficiency and green environmental demands, and reducing the harm of water pollution to public health [7].

In technological development, traditional electrochemical and optical monitoring technologies and their products are relatively mature and have a high market penetration rate. Advances in small light source technology have also accelerated the development of optical monitoring equipment. Micro-Electro-Mechanical System (MEMS) technology with Lab-on-chip and multifunctional integration advantages is also gradually maturing in water quality monitoring applications and has growth potential. Biosensing has the potential to monitor toxicity and biological pollutants, but its technological maturity is low, and nano-sensing equipment, which has the advantage of miniaturization, is still in the early stages of technological development.

Unfortunately, the implementations of current wastewater treatment technologies lack an integrated system [8], [9]. Given trends such as energy shortages, sustainability demands, and increased awareness, as well as operational difficulties in utility water, how to develop water treatment towards low-carbon, enhance energy use efficiency, and combine with renewable energy presents new opportunities for the future water treatment industry [10], [11]. This conceptual paper proposes the planning and application of a wastewater treatment system aimed at improving treatment efficiency and significantly reducing operating costs, taking proactive measures to ensure the stable operation of the wastewater treatment system, achieving intelligent management of the wastewater treatment system, and promoting the industry towards more efficient and environmentally friendly directions.

2 | Literature Review

2.1 | AI for Early Warning and Decision-Making Systems

In the past five years, significant progress has been made in integrating wastewater treatment with Artificial Intelligence (AI) for early warning and decision-making systems [12], [13]. With the rapid pace of urbanization and the increasing severity of environmental pollution, traditional wastewater treatment methods can no longer meet the demands of modern society [14]. Literature indicates that AI technology plays a crucial role in improving the efficiency and effectiveness of wastewater management processes. By introducing technologies such as machine learning, deep learning, and big data analysis, the level of intelligence in wastewater treatment systems has significantly increased. This paper reviews the research outcomes in related fields over the past five years, exploring the current applications, challenges, and future development directions of AI technology in wastewater treatment [15–17].

Research shows that machine learning algorithms are practical in predicting treatment plant performance, optimizing operational parameters, and identifying potential system failures before they occur [18–21]. For example, applied machine learning models to predict the effluent quality of wastewater treatment plants, showing that the model can effectively improve prediction accuracy and help managers take preemptive measures. Specifically, neural networks and support vector machines have been successfully used to predict effluent quality, enabling proactive adjustments to treatment protocols. These models can also dynamically adjust treatment parameters by learning from extensive historical data, thereby optimizing treatment outcomes [4]. In addition, these models achieve comprehensive monitoring and optimization of the wastewater treatment process by combining multi-source data (such as sensor data and historical operational data). AI technology can handle complex multi-factor decision-making problems, helping managers make more scientific and reasonable decisions. For instance, when dealing with the coordinated treatment of multiple pollutants, AI technology can help determine the optimal combination of treatment parameters, thereby improving treatment efficiency and effectiveness. Furthermore, AI technology can help predict future wastewater flow and pollutant concentrations, providing support for long-term planning and resource allocation [22], [23].

Big data technology has also achieved significant results in wastewater treatment. AI technology makes it possible to process large datasets, providing in-depth insights into complex treatment dynamics and supporting the development of more sustainable practices [8], [21]. Their research demonstrated how big data analysis can optimize treatment parameters and improve the efficiency and effectiveness of wastewater treatment. Specifically, by deeply mining and analyzing historical data, researchers can identify key factors affecting treatment outcomes, thereby adjusting operational strategies to achieve optimal treatment results.

AI applications in wastewater treatment also include fault detection and diagnosis. Traditional fault detection methods usually rely on fixed thresholds or simple statistical models, which are difficult to handle in complex and variable operating environments. In contrast, AI technology can establish more flexible and accurate fault detection models by learning from extensive historical data. For example, used deep learning algorithms to identify and predict equipment failures, achieving good results in some studies. These AI models can automatically identify abnormal operating states and provide fault diagnosis and early warnings, thereby reducing operational costs and environmental risks [24], [25]. Specifically, AI technology in fault detection includes the following aspects. First, by monitoring and analyzing equipment operating data in real-time, AI models can timely detect abnormal operating states and generate early warning signals. This allows operators to take measures before issues escalate, avoiding broader failures and losses. Second, AI models can deeply mine historical data to identify potential fault patterns and causes.

This information can help managers conduct targeted maintenance and upkeep, improving equipment reliability and lifespan. Finally, by integrating information from different data sources, AI technology can provide more comprehensive and accurate fault diagnosis and prediction, helping managers better cope with complex operating environments [26]. In practical applications, AI technology has already been successfully used in multiple wastewater treatment plants. For instance, a wastewater treatment plant in Beijing improved the stability and reliability of wastewater treatment by introducing an AI early warning system. This system can monitor various indicators in the treatment process in real time and issue warnings when abnormalities are detected, helping operators take swift measures. This system can provide optimization suggestions based on historical data and operational patterns, helping managers better adjust operational parameters and improve treatment efficiency.

Existing research further indicates that future research should improve these technologies, focusing on enhancing model accuracy, expanding prediction capabilities, and integrating AI with other emerging technologies, such as the Internet of Things (IoT) and advanced sensor networks [18]. The introduction of IoT technology will enable more sensor data to be collected and processed in real time, further increasing the intelligence level of wastewater treatment. The development of IoT technology provides more data sources for wastewater treatment systems, helping AI models make more accurate predictions and decisions. Additionally, through IoT technology, wastewater treatment systems can achieve remote monitoring and management, improving operational efficiency and management levels.

In summary, AI technology in wastewater treatment has broad prospects and great potential to improve treatment efficiency, reduce operational costs, and minimize environmental risks. Existing studies suggest that future research and applications will further advance this field, providing technical support for more sustainable wastewater management. Specifically, researchers need to conduct in-depth research and exploration in the following areas: first, improving the accuracy and stability of AI models, especially when dealing with complex and variable wastewater environments. Second, developing and applying more flexible and adaptive AI technology to meet wastewater treatment needs in different scenarios. Finally, enhancing the interpretability and transparency of AI technology allows operators to understand better and apply these technologies. AI technology in wastewater treatment has broad prospects and potential, and future research and applications will further advance this field, providing technical support for more sustainable wastewater management [27–30].

3 | Concept Development of AI Early Warning and Decision-Making Systems

3.1 | AI and Decision-Making Systems: Conceptual Development

In wastewater management systems, various substances, energy, structures, forms, functions, and controls are manifested through the operation process. Therefore, grasping the dynamic behaviour of wastewater management systems is key to ensuring the effectiveness of their operation. The operation of wastewater treatment systems is dynamic and highly complex. Besides the continuously changing characteristics of the influent wastewater in terms of volume and quality over time, the procedural control of treatment subsystems is influenced by factors such as microbial metabolism, mechanical operation, and environmental condition variations. Any deficiency or change in one aspect can affect the effectiveness of water treatment and the stability of the system. This study proposes that wastewater management systems must develop a dynamic feedback control mechanism that is real-time, visible, and trend-based.

Moreover, there is usually an exchange of materials, energy, and information between wastewater management systems and their surrounding environment. Environmental changes can cause changes in system characteristics, which in turn lead to changes in the interactions and relationships among the internal units, processes, and subsystems of the system. Therefore, wastewater management systems must also have reporting systems, self-adaptive, and self-learning systems to maintain their ability to adapt to objective environments.

All levels of wastewater management systems must implement control measures within their respective wastewater management mechanisms to achieve their established goals. Therefore, in terms of the system management aspect of wastewater management systems, the key areas include: 1) equipment maintenance, 2) equipment and site inspections, 3) compliance with water quality standards and regulations, and 4) energy and cost savings to meet sustainable development principles, as shown in *Fig. 1*.

Additionally, regarding the operation management aspect of wastewater management systems, in recent years, the increased standards for wastewater control and the growing demand and degree of water recycling and reuse have made the original issues of operation, maintenance, and management more complex. This includes increased requirements for human resources, proper maintenance rates of equipment, equipment renewal, standard upgrades, control of consumables and chemicals, and energy-saving and carbon reduction.

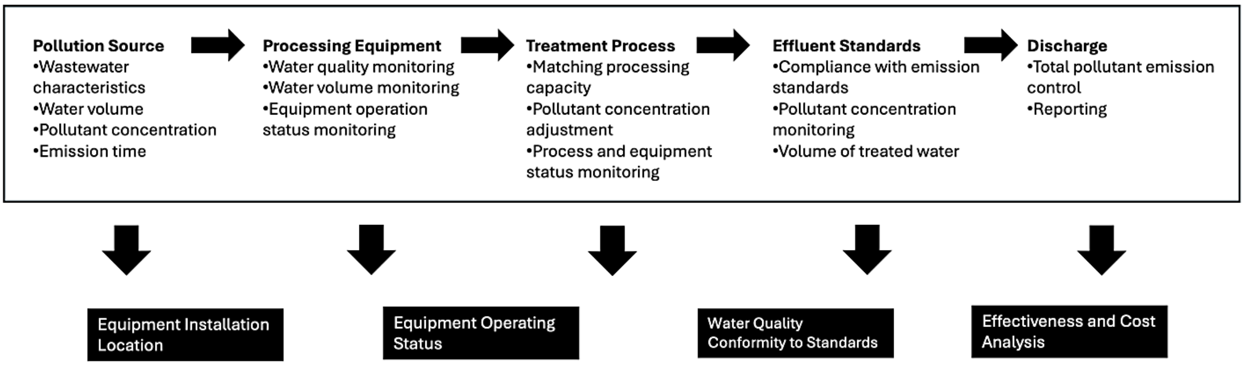

Fig. 1. Analysis of wastewater treatment management system management needs.

3.2 | The Process and Expected Outcomes of Implementing the Systems

The application of smart AIoT includes three major themes: prediction and decision-making for water treatment systems, optimization of water treatment operation procedures, and smart water treatment management platforms. These are also the core businesses of this study's AI smart wastewater management system (*Fig. 2*).

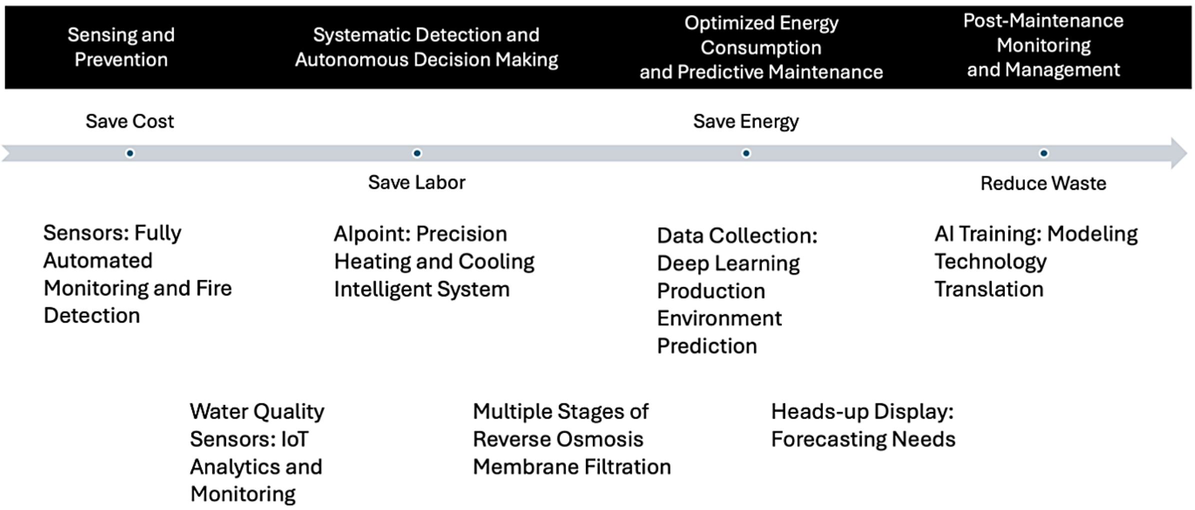

Fig. 2. Scope of services and benefits of AI smart water treatment systems.

The implementation process can be divided into two scenarios:

I. Establishing a new system and introducing the AI model based on the current situation: AI engineers and scholars will introduce a packaged AI monitoring and management model, which will be adjusted according to the current situation to become a customized model.

II. Improving the existing wastewater management system and then introducing the AI model: AI engineers, on-site operators, and external experts will work together to introduce the model, making it a practical, customized system. By using a smart AI cloud platform to collect past big data and integrate it with AI hardware processing systems, machine learning will compute not only past experience values but also generate sudden event models, allowing the AI to produce more processing scenarios and enhance the system's processing capabilities.

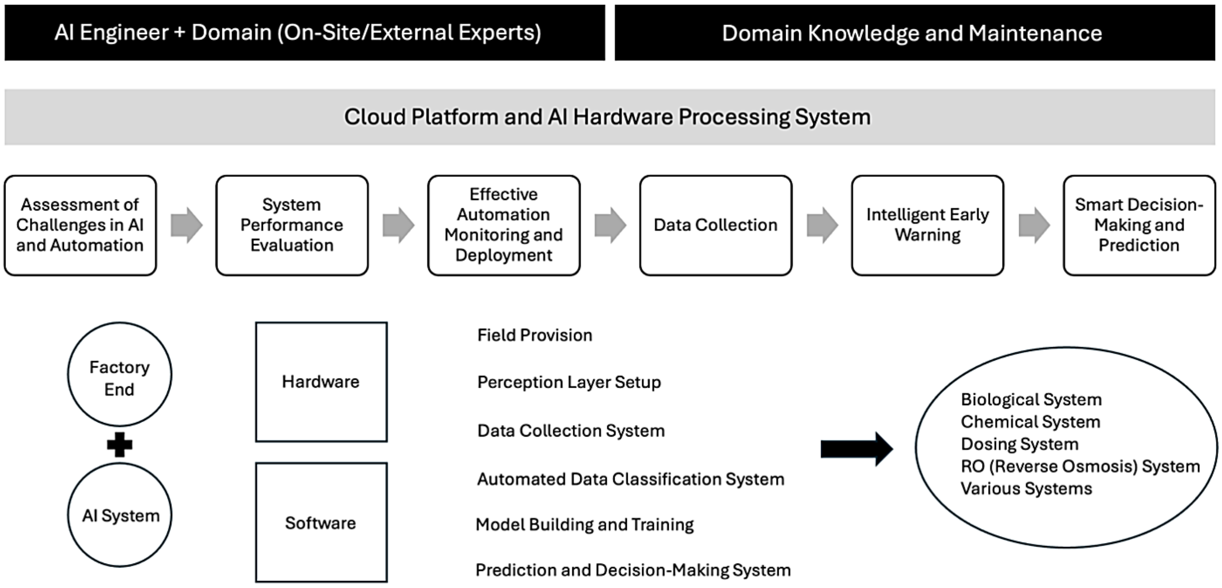

Fig. 3. AI implementation model and process.

The processes based on the two models include: 1) identifying pain points, generating evaluations, and introducing AI systemization, 2) evaluating and simulating system effects, 3) effective automation monitoring and point placement, 4) data collection and generation, 5) intelligent early warning, and 6) smart prediction and decision-making.

In the modelling process, experienced on-site operators will provide valuable past experiences, combined with the AI R&D team's intelligence, to upgrade hardware with AI (faster computation, larger memory, better heat dissipation), enhance software models (smarter software, generated learning), and provide real field data. By establishing a sensory coverage layer combined with a data collection system and upgrading through AI, the data automatic classification system will be optimized, and an AI processing model and autonomous training will be established, becoming a more accurate prediction and decision system. This will upgrade traditional biological, chemical, dosing, RO, and other systems to be intelligent, preparing for future processing capabilities (*Fig. 3*).

Integrating intelligent management and monitoring, the developed AI precision dosing intelligent system is expected to achieve the following benefits:

I. Reducing operational manpower: automated systems reduce reliance on manpower, lowering the need for operation and monitoring.

II. Reducing chemical dosing: precision measurement and control ensure optimal dosing each time, reducing chemical waste.

III. Reducing sludge production: optimizing the dosing process reduces unnecessary chemical reactions, thus lowering sludge production.

IV. Reducing carbon emissions/energy saving: intelligent systems enhance overall operational efficiency, reducing energy consumption and thereby lowering carbon emissions.

V. Extending system life: precise dosing control and preventive maintenance reduce equipment wear, extending the system's lifespan.

VI. Automated system prevention and maintenance: the system can monitor operational status in real-time, automatically warn of potential issues, and perform preventive maintenance, reducing failures and downtime.

VII. Lowering conductivity: precision chemical control reduces unnecessary chemical reactions, lowering solution conductivity.

The digitization levels of sewage and wastewater plants vary; therefore, this study suggests customizing solutions for different customers. For plants that are not yet digitized, IoT equipment and hardware/software systems should be built. For plants that already have IoT, AI technology should be introduced to address factory-specific pain points and improve overall wastewater treatment efficiency.

Combining rich past experience in water treatment with AI experts, factories only need to provide water quality data to achieve AI prediction and decision-making. In practice, some factories have stringent cybersecurity requirements; the AI smart cloud platform can connect data collection hardware directly to the factory, with data returning without being stored in the cloud. The system will automatically classify and filter calculation models to find the most suitable model, then connect to the system to produce prediction and decision results. Additionally, the cloud platform uses blockchain encryption, ensuring secure data connection. The factory follows the same steps for quick integration. Moreover, the backend monitoring system can help with early warnings for water treatment or water recycling systems, including sensor failure prevention, automatic protection, and backend model retraining. The project duration is approximately 3-6 months, followed by model adjustments based on system conditions, integrating with after-sales service.

Furthermore, in the past, defect detection in the chemical fibre industry mostly relied on manual inspection, with a detection rate of 80%-90%. After introducing AI optical detection technology, the detection rate can be improved to over 95%. Subsequent manual re-inspection or spot checks can significantly improve defect detection rates by about 10%, saving considerable manpower with substantial benefits.

Additionally, in past wastewater treatment plant operations, water quality sampling results were observed first. Equipment dynamic adjustments were manually conducted by experienced technicians, often leading to energy waste due to the lack of real-time monitoring. After introducing AI, the AI model, based on monitoring results, deduces the output required for motors or equipment, controlling the water quality within a certain standard range and is estimated to save more than 20% in energy consumption. Both municipal sewage plants and water supply companies need intelligent water service platforms to assist in monitoring wastewater treatment conditions.

4 | Discussion

4.1 | General Discussion

The application of AI in water resource management demonstrates broad prospects and significant strategic importance. By integrating computer technology and AI, we can achieve more precise data analysis, real-time predictions, and decision-making, which are crucial for addressing the challenges posed by climate change and extreme weather events. AI technology can enhance the efficiency and effectiveness of water resource management, promote ecological protection and environmental sustainability, and achieve harmonious coexistence between humans and nature.

With the intensification of global climate change and the increasing frequency of extreme weather events, water resource management faces unprecedented challenges. Traditional methods often rely on historical data and experience, which can be inadequate in rapidly changing environments. The introduction of AI technology provides a more flexible and efficient solution. Through real-time data analysis and forecasting, AI can help decision-makers quickly respond to emergencies, reduce disaster losses, and ensure the safety of people's lives and property. Moreover, AI can assist in long-term water resource planning, developing more scientific and sustainable strategies to ensure the long-term sustainability of water resources.

4.2 | Theoretical and Practical Implications

Theoretically, this study emphasizes the potential of AI technology in handling complex water resource systems and provides a foundational module demonstrating how AI can be applied in time series forecasting, water quality monitoring, and short- and long-term operational strategies. These applications can improve the accuracy and efficiency of data analysis, offering more detailed and comprehensive data perspectives to help better understand and manage the dynamic changes in water resource systems.

Practically, AI technology can provide real-time data analysis and forecasting, assisting decision-makers in quickly formulating responses to extreme weather events and facilitating long-term water resource planning to ensure sustainable utilization. For instance, during rainfall and flood events, AI can help decision-makers quickly formulate response measures through real-time data analysis and forecasting, reducing disaster losses. By implementing the integrated system, AI can be used for monitoring and evaluating water quality, predicting groundwater and river levels, exploring the interactions between rivers and ecosystems, and optimizing the short- and long-term operational strategies of reservoirs.

4.3 | Limitations and Suggestions for Future Research

Despite the promising prospects of AI in water resource management, there are challenges and limitations:

I. Data quality and completeness: the accuracy of AI models relies on high-quality data. However, in current water resource management, data collection may be incomplete or of low quality, affecting the accuracy and reliability of AI models.

II. Interdisciplinary collaboration: applying AI in water resource management requires knowledge from multiple disciplines, such as hydrology, environmental science, and computer science. However, current research lacks sufficient interdisciplinary collaboration, potentially limiting the comprehensive application of the technology.

III. Technology and cost: implementing and maintaining AI technology requires high costs and technical support, which might be challenging for resource-limited regions and institutions. Moreover, AI application necessitates professional technical personnel, which may be a challenge in some areas.

Future studies are encouraged to

I. Enhance data collection and management: establish more comprehensive and high-quality data collection systems to ensure AI models can analyze and predict based on accurate and reliable data. This includes improving sensor technology, enhancing data collection accuracy and range, and establishing standardized data management systems.

II. Promote interdisciplinary collaboration: strengthen interdisciplinary cooperation in water resource management, information engineering, and ecological environment fields to develop and apply AI technology jointly. Interdisciplinary collaboration can provide more comprehensive and in-depth perspectives, fostering innovation and application.

III. Address the technological innovation and optimization: continuously research and optimize AI technologies, such as neural networks, fuzzy inference, and genetic algorithms, to address increasingly complex challenges in water resource management. This includes developing more efficient and accurate algorithms to enhance AI models' performance and interpretability.

IV. Promote and educate: increase awareness and education on AI applications in water resource management, cultivate more professionals, and promote widespread application. This includes organizing professional training and seminars to enhance the skills and knowledge of relevant practitioners.

V. Conduct cost-benefit analysis: conduct detailed cost-benefit analyses to ensure the economic benefits of implementing AI technology and formulate related policies and funding support plans. This helps improve the sustainability and broad application of technology, ensuring effective promotion in different regions and institutions.

5 | Conclusion

The application of AI technology in water resource management offers a new solution that can significantly enhance the efficiency and effectiveness of water resource management, promoting ecological protection and environmental sustainability [31]. Future research should focus more on interdisciplinary collaboration, integrating the latest technologies and data analysis techniques, and continually exploring and innovating to address the increasingly complex challenges in water resource management. Through these initiatives, it is anticipated that more efficient and sustainable water resource management will be achieved. This will ensure the preservation of water resources and ecological health for future generations and contribute significantly to the attainment of global sustainable development goals.

Author Contributaion

Conceptualization, Hung-Li Chang; Validation, Hung-Li Chang and Ching-Jui Keng; investigation, Han-Ling Jiang; resources, Yu-Lun Liu; data maintenance, Yu-Lun Liu; writing-creating the initial design, Yu-Lun Liu; writing-reviewing and editing, Han-Ling Jiang and Hung-Li Chang; visualization, Han-Ling Jiang; monitoring, Ching-Jui Keng; project management, Hung-Li Chang. All authors have read and agreed to the published version of the manuscript.

Funding

It is declared that this research involved no external funding and was undertaken solely with the researchers' own means.

Data Availability

All the data are available in this paper.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Stokes, J. R., & Horvath, A. (2010). Supply-chain environmental effects of wastewater utilities. *Environmental research letters*, *5*(1), 14015. DOI:10.1088/1748-9326/5/1/014015

[2] Martínez-Espiñeira, R., & García-Valiñas, M. Á. (2013). Adopting versus adapting: adoption of water-saving technology versus water conservation habits in Spain. *International journal of water resources development*, *29*(3), 400–414. DOI:10.1080/07900627.2012.721695

[3] Gupta, V. K., Ali, I., Saleh, T. A., Nayak, A., & Agarwal, S. (2012). Chemical treatment technologies for wastewater recycling - an overview. *RSC advances*, *2*(16), 6380–6388. DOI:10.1039/c2ra20340e

[4] Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., … & Williams, M. D. (2021). Artificial Intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International journal of information management*, *57*, 101994. DOI:10.1016/j.ijinfomgt.2019.08.002

[5] Zhuang, C., Liu, J., & Zhang, L. (2022). Connotation, architecture and enabling technology of industrial 5.0. *Journal of mechanical engineering*, *58*(18), 75–87. DOI:10.1088/1748-9326/5/1/014015

[6] Wang, J., Zhang, L., Hou, R., & Zhang, C. (2013). Analysis and comparison between digital and smart water conservancy. *Geo-informatics in resource management and sustainable ecosystem: international symposium, GRMSE 2013, Wuhan, China, November 8-10, 2013, Proceedings, Part II 1* (pp. 424–434). Springer. https://doi.org/10.1007/978-3-642-41908-9_44

[7] Schwarzenbach, R. P., Egli, T., Hofstetter, T. B., Von Gunten, U., & Wehrli, B. (2010). Global water pollution and human health. *Annual review of environment and resources*, *35*(1), 109–136. DOI:10.1146/annurev-environ-100809-125342

[8] Chen, J., Chen, S., Fu, R., Li, D., Jiang, H., Wang, C., … & Hicks, B. J. (2022). Remote sensing big data for water environment monitoring: current status, challenges, and future prospects. *Earth's future*, *10*(2), e2021EF002289. DOI:10.1029/2021EF002289

[9] Voulvoulis, N. (2018). Water reuse from a circular economy perspective and potential risks from an unregulated approach. *Current opinion in environmental science and health*, *2*, 32–45. DOI:10.1016/j.coesh.2018.01.005

[10] Geissdoerfer, M., Savaget, P., Bocken, N. M. P., & Hultink, E. J. (2017). The circular economy-a new sustainability paradigm? *Journal of cleaner production*, *143*, 757–768. DOI:10.1016/j.jclepro.2016.12.048

[11] Morseletto, P., Mooren, C. E., & Munaretto, S. (2022). Circular economy of water: definition, strategies and challenges. *Circular economy and sustainability*, *2*(4), 1463–1477. DOI:10.1007/s43615-022-00165-x

[12] Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: challenges, opportunities, and a research agenda. *International journal of information management*, *53*, 102104. DOI:10.1016/j.ijinfomgt.2020.102104

[13] Zhang, S., Jin, Y., Chen, W., Wang, J., Wang, Y., & Ren, H. (2023). Artificial intelligence in wastewater treatment: a data-driven analysis of status and trends. *Chemosphere*, *336*, 139163. DOI:10.1016/j.chemosphere.2023.139163

[14] Borja, Á., Franco, J., Valencia, V., Bald, J., Muxika, I., Belzunce, M. J., & Solaun, O. (2004). Implementation of the European water framework directive from the Basque country (northern Spain): a methodological approach. *Marine pollution bulletin*, *48*(3–4), 209–218. DOI:10.1016/j.marpolbul.2003.12.001

[15] Hernández-Chover, V., Castellet-Viciano, L., Fuentes, R., & Hernández-Sancho, F. (2023). Circular economy and efficiency to ensure the sustainability in the wastewater treatment plants. *Journal of cleaner production*, *384*, 135563. DOI:10.1016/j.jclepro.2022.135563

[16] Bahramian, M., Dereli, R. K., Zhao, W., Giberti, M., & Casey, E. (2023). Data to intelligence: the role of data-driven models in wastewater treatment. *Expert systems with applications*, *217*, 119453. DOI:10.1016/j.eswa.2022.119453

[17] Babaei, A. A., Tahmasebi Birgani, Y., Baboli, Z., Maleki, H., & Ahmadi Angali, K. (2023). Using water quality parameters to prediction of the ion-based trihalomethane by an artificial neural network model. *Environmental monitoring and assessment*, *195*(8), 917. DOI:10.1007/s10661-023-11503-3

[18] Sinharoy, A., Mahanty, B., Behera, S. K., Mehta, M., Mantri, S., Das, R., … & Pakshirajan, K. (2024). Modelling selenite and chemical oxygen demand removal in an inverse fluidized bed bioreactor using genetic algorithm optimized artificial neural network. *Journal of chemical technology and biotechnology*, *99*(1), 247–258. DOI:10.1002/jctb.7532

[19] Sadek, A. H., Fahmy, O. M., Nasr, M., & Mostafa, M. K. (2023). Predicting Cu(II) adsorption from aqueous solutions onto nano zero-valent aluminum (nZVAl) by machine learning and artificial intelligence techniques. *Sustainability*, *15*(3), 2081. DOI:10.3390/su15032081

[20] Adibimanesh, B., Polesek-Karczewska, S., Bagherzadeh, F., Szczuko, P., & Shafighfard, T. (2023). Energy consumption optimization in wastewater treatment plants: machine learning for monitoring incineration of sewage sludge. *Sustainable energy technologies and assessments*, *56*, 103040. DOI:10.1016/j.seta.2023.103040

[21] Chen, K., Chen, H., Zhou, C., Huang, Y., Qi, X., Shen, R., … & Ren, H. (2020). Comparative analysis of surface water quality prediction performance and identification of key water parameters using different machine learning models based on big data. *Water research*, *171*, 115454. DOI:10.1016/j.watres.2019.115454

[22] Xu, B., Pooi, C. K., Tan, K. M., Huang, S., Shi, X., & Ng, H. Y. (2023). A novel long short-term memory artificial neural network (LSTM)-based soft-sensor to monitor and forecast wastewater treatment performance. *Journal of water process engineering*, *54*, 104041. DOI:10.1016/j.jwpe.2023.104041

[23] Yang, S. S., Yu, X. L., Ding, M. Q., He, L., Cao, G. L., Zhao, L., … & Ren, N. Q. (2021). Simulating a combined lysis-cryptic and biological nitrogen removal system treating domestic wastewater at low C/N ratios using artificial neural network. *Water research*, *189*, 116576. DOI:10.1016/j.watres.2020.116576

[24] Škrjanc, I. (2009). Confidence interval of fuzzy models: an example using a wastewater treatment plant. *Chemometrics and intelligent laboratory systems*, *96*(2), 182–187. DOI:10.1016/j.chemolab.2009.01.009

[25] Obiuto, N. C., Olu-lawal, K. A., Ani, E. C., Ugwuanyi, E. D., & Ninduwezuor-Ehiobu, N. (2024). Chemical engineering and the circular water economy: simulations for sustainable water management in environmental systems. *World journal of advanced research and reviews*, *21*(3), 1–9.

[26] Salari, M., Alahabadi, A., Rahmani-Sani, A., Miri, M., Yazdani-Aval, M., Lotfi, H., … & Darvishmotevalli, M. (2024). A comparative study of response surface methodology and artificial neural network based

algorithm genetic for modeling and optimization of EP/US/GAC oxidation process in dexamethasone degradation: application for real wastewater, electrical energy consump. *Chemosphere*, *349*, 140832. https://doi.org/10.1016/j.chemosphere.2023.140832

[27] Sauvé, S., Lamontagne, S., Dupras, J., & Stahel, W. (2021). Circular economy of water: tackling quantity, quality and footprint of water. *Environmental development*, *39*, 100651. DOI:10.1016/j.envdev.2021.100651

[28] Mihai, F. C., Minea, I., & Ulman, S. R. (2023). Water resources preservation through circular economy: the case of Romania. In *Water management and circular economy* (pp. 143–176). Elsevier. DOI: 10.1016/B978-0-323-95280-4.00002-3

[29] Zarei, M. (2020). Wastewater resources management for energy recovery from circular economy perspective. *Water-energy nexus*, *3*, 170–185. DOI:10.1016/j.wen.2020.11.001

[30] Fernandes, E., & Cunha Marques, R. (2023). Review of water reuse from a circular economy perspective. *Water*, *15*(5), 848. DOI:10.3390/w15050848

[31] Dziedzic, M., Gomes, P. R., Angilella, M., Asli, A. El, Berger, P., Charmier, A. J., … & Tsukada, S. (2022). International circular economy strategies and their impacts on agricultural water use. *Cleaner engineering and technology*, *8*, 100504. DOI:10.1016/j.clet.2022.100504