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Machine learning in Industrial Wastewater Treatment: A Bibliometric Analysis of Research Trends and Future Prospects

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Abstract

Industrial wastewater treatment is a critical area of environmental research and engineering, with increasing attention on advanced technologies to enhance efficiency and sustainability. Among these technologies, machine learning (ML) has emerged as a powerful tool for optimizing treatment processes, predicting contaminant behavior, and improving decision-making in wastewater management. This study conducts a bibliometric analysis to examine research trends, key contributions, and future directions in the application of machine learning for industrial wastewater treatment. By analyzing scholarly publications, citation patterns, and keyword occurrences, we identify the most influential studies, prominent authors, and leading research institutions driving innovation in this field. The findings highlight the growing integration of ML techniques, such as artificial neural networks (ANNs), support vector machines (SVMs), and deep learning, in contaminant removal, process optimization, and real-time monitoring. Furthermore, this study discusses the challenges and future opportunities for expanding the role of ML in industrial wastewater treatment, emphasizing the need for data-driven models, hybrid approaches, and real-world applications. The insights derived from this bibliometric analysis provide a comprehensive understanding of the current research landscape and pave the way for future advancements in AI-driven wastewater treatment solutions.

Keywords: *Machine Learning, Industrial Wastewater Treatment, Bibliometric Analysis, Research Trends, Artificial Intelligence, Environmental Engineering, Contaminant Removal*

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1. Introduction

In recent years, the intersection of artificial intelligence (AI) and wastewater treatment has gained increasing attention, offering transformative potential for environmental management. As global populations rise alongside urbanization and industrial growth, the demand for more efficient and sustainable wastewater treatment solutions has become more urgent than ever(Chowdhury et al., 2022; Kato & Kansha, 2024; Mattia, 1862). Traditional treatment methods often face constraints in terms of effectiveness, energy use, and economic viability(J. Wang et al., 2019).

Water is an essential resource for human survival and industrial processes, but it faces growing risks from pollutants originating from both natural and human activities (Ahmad et al., 2022; Li et al., 2025; Lim & Aris, 2014). Factors such as rapid population growth, industrial expansion, urbanization, and the widespread effects of climate change have significantly intensified water pollution, particularly through nutrient discharge into aquatic ecosystems(Liu et al., 2017; Maurya et al., 2024). These pressures have led to both qualitative and quantitative limitations on water resources(Sardooi et al., 2024). While water scarcity is a major issue in developing countries, even highly industrialized nations face persistent challenges in maintaining adequate potable water supplies due to pollution from urban and industrial sources(Karthikeyan et al., 2017; Singha et al., 2023). The high-water consumption of various industries exacerbates environmental degradation by releasing toxic and non-biodegradable pollutants into the environment. Addressing global water scarcity has thus become one of the most urgent challenges of the 21st century(Eldoma et al., 2024; Khalid et al., 2017; Zarzzeka et al., 2024; Y. Zhang et al., 2022).

Efficient wastewater treatment is crucial not only for maintaining a safe and sustainable water supply but also for protecting ecosystems and public health. However, traditional treatment methods often struggle to effectively remove emerging contaminants(Graça & Rodrigues, 2022; Khalid et al., 2017). In response to these challenges, wastewater reclamation and reuse have been recognized as key strategies for mitigating water shortages(Graça & Rodrigues, 2022; Sin et al., 2021). This approach plays a critical role in sustainable water resource management by enabling the reuse of treated wastewater across various applications(Al-Zghoul et al., 2023). As a result, there is a growing need to enhance and modernize wastewater treatment technologies through innovative and data-driven approaches(Lowe & Qin, 2022; Parvulescu et al., 2022). A major concern in this context is ensuring water quality, a challenge compounded by the limitations of existing technologies in providing comprehensive analytical assessments(Abas et al., 2013; Baarimah et al., 2024; Babel & Kurniawan, 2003). For years, researchers have been exploring methods to improve wastewater treatment, focusing on developing efficient, cost-effective, and intelligent models to address its inherent challenges(Gao et al., 2024; Long et al., 2022; J. Wang et al., 2019; Wei et al., 2020; Wu et al., 2023; W. Zhang et al., 2025; X. Zhang et al., 2023).

The integration of AI into wastewater treatment introduces a transformative approach to improving efficiency, precision, and automation. Utilizing machine learning (ML) algorithms, predictive modeling, and advanced data analytics, AI can streamline numerous facets of wastewater treatment, such as contaminant detection, process optimization, resource recovery, and system performance enhancement. By harnessing AI-powered insights, wastewater treatment plants (WWTPs) can boost operational effectiveness, minimize environmental impacts, and adhere to increasingly strict regulatory standards(Fu et al., 2022; Kumar et al., 2023). While ML enables systems to learn and adapt based on data patterns, AI allows algorithms to perform tasks and make decisions that traditionally required human expertise(Gomaa, Khafaga, et al., 2024; Kumar et al., 2023; Lotfy et al., n.d.). These intelligent technologies have been widely adopted in both academic research and industrial applications due to their ability to streamline complex processes and enhance decision-making in wastewater treatment(Fu et al., 2022; Kumar et al., 2023).

Machine learning (ML) has shown great promise in tackling critical challenges like pollutant detection, process optimization, and system control in wastewater treatment. The flexibility and efficiency of AI, ML, and other advanced technologies enable them to address complex issues, reducing operational costs and enhancing system resilience. While existing studies have demonstrated the effectiveness of AI-based models in wastewater treatment, much of the research focuses on specific techniques or process designs, with limited exploration of broader AI frameworks, their benefits, challenges, and practical implementation considerations. Most prior work emphasizes the technical performance of ML algorithms, often neglecting real-world challenges such as data constraints, ethical concerns, scalability, and regulatory compliance. Furthermore, there is a notable gap in critically assessing the risks of over-reliance on automated systems in a vital field like water treatment.

This study seeks to address this gap by performing a detailed bibliometric analysis to explore research trends, identify significant publications, and propose future directions for the application of AI and ML in wastewater treatment. The objectives of this research are:

- Synthesizing insights from existing literature on how ML can help address water scarcity and wastewater treatment challenges.
- Identifying key obstacles and ethical concerns associated with adopting ML in wastewater treatment systems.
- Proposing a research roadmap for future advancements in AI-driven wastewater treatment technologies.

This paper provides a critical analysis of the current literature, delving into the various applications of AI in wastewater treatment, including real-time monitoring, automated control, predictive modeling, and process optimization. It also investigates the key challenges and barriers to the broader adoption of AI in real-world wastewater treatment, such as data limitations, model reliability, scalability, and regulatory compliance. By addressing these critical issues, the study aims to offer valuable insights to researchers, industry practitioners, policymakers, and stakeholders looking to harness AI for addressing complex environmental challenges in wastewater management. Through an in-depth evaluation of existing research and potential future directions, this paper seeks to promote interdisciplinary collaboration and drive innovation in AI-based wastewater treatment solutions, ultimately contributing to more efficient, sustainable, and resilient water management systems for the benefit of both humanity and the environment.

2. Methodology

This study employed a bibliometric and qualitative review approach, adhering to the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to ensure transparency and reproducibility. The data collection and analysis were conducted using Scopus, and the visualization and clustering analysis were performed using VOSviewer.

2.1. Data Source and Search Strategy

The literature search was conducted using the Scopus database, chosen for its comprehensive coverage of peer-reviewed journal articles across scientific and technical disciplines. To identify relevant publications, the following search query was applied: TITLE-ABS-KEY ("Machine learning" OR "Artificial intelligence" OR "AI") AND ("Industrial Wastewater Treatment" OR "Wastewater Treatment" OR "heavy metal removal") AND LIMIT-TO (SUBJAREA, "ENGI") AND LIMIT-TO (LANGUAGE, "English"). The search was restricted to journal articles published between 2014 and 2025 and written in English. This initial search resulted in a total of 1,842 documents.

2.2. Screening and Selection Criteria

The screening and filtering process adhered to the PRISMA guidelines and comprised four key stages: identification, screening, eligibility, and inclusion. As illustrated in Fig. 1 (PRISMA Flow Diagram), the process began with the identification stage, during which 1,842 articles were retrieved from selected databases. In the screening stage, 58 duplicate records and non-journal items, such as editorials and errata, were excluded, resulting in 1,784 articles. During the eligibility phase, the titles, abstracts, and full texts of these articles were thoroughly reviewed to assess their relevance to the research scope. Finally, in the inclusion stage, a total of 499 articles were retained based on specific inclusion and exclusion criteria. The inclusion criteria required articles to be peer-reviewed journal publications that applied machine learning (ML) techniques specifically to wastewater treatment, presented empirical data, modeling approaches, or algorithm development, and reported measurable outcomes such as prediction accuracy or process optimization. Conversely, the exclusion criteria eliminated articles that did not involve ML (e.g., those based solely on statistical or mechanistic models), focused exclusively on drinking water or water supply, were non-English or lacked accessible full texts, or were review articles without original data or methodological contributions.

2.3. Data Analysis Tools and Techniques

The final dataset, consisting of 499 articles, was exported from Scopus in BibTeX format and analyzed using a combination of tools and methods. VOSviewer was employed for network visualization, including co-authorship networks, keyword co-occurrence, country collaboration, and citation clusters. Microsoft Excel was used to perform descriptive statistical analyses, such as tracking annual publication trends, identifying top contributing journals, and evaluating citation metrics. Additionally, a qualitative content analysis was conducted to examine the practical applications of machine learning in wastewater treatment, with particular attention to algorithm performance, implementation contexts, and noted limitations. Clustering algorithms embedded within VOSviewer were applied using the LinLog/modularity optimization technique. Thresholds for minimum occurrences were set strategically to ensure a balance between comprehensiveness and visual clarity in the generated bibliometric maps.

3. Results

Bibliometric analysis is a statistical approach used to quantify and evaluate the emerging trends within a particular field of study(Abuhassna et al., 2022; Abuhassna & Yahaya, 2022). Bibliometric analysis has been applied to evaluate academic outputs across multiple disciplines (Chen et al., 2019). The search, conducted on the Scopus database from 2014 to 2025, utilized various search fields such as Author keywords, Title, Abstract, Author, and Keywords Plus. The search employed a combination of keywords using AND/OR logic, including terms like (("Machine learning" OR "Artificial intelligence" OR "AI") AND (" Industrial Wastewater Treatment" OR "Wastewater Treatment" OR " heavy metal removal")). The results were assessed based on titles and abstracts to ensure coherence with the article's theme and core topic.

The analysis utilized Scopus analysis and VOS viewer for data visualization. Graphs were generated using Microsoft Excel. Various details were extracted for each document, including (1) the number of documents per year, (2) average citations of articles per year, (3) author keywords and frequently used words in titles, (4) journals of publication for each article, (5) science categories, (6) most cited articles, (7) authors and coauthors for each article, (8) H-index for top 30 authors, (9) affiliation details for authors and coauthors, (30) countries of the authors, and (11) H-index for top 20 journals,. Bibliographic maps were generated using VOS viewer software, encompassing keywords co-occurrence, countries co-authorship maps, and bibliographic coupling for countries and affiliations.

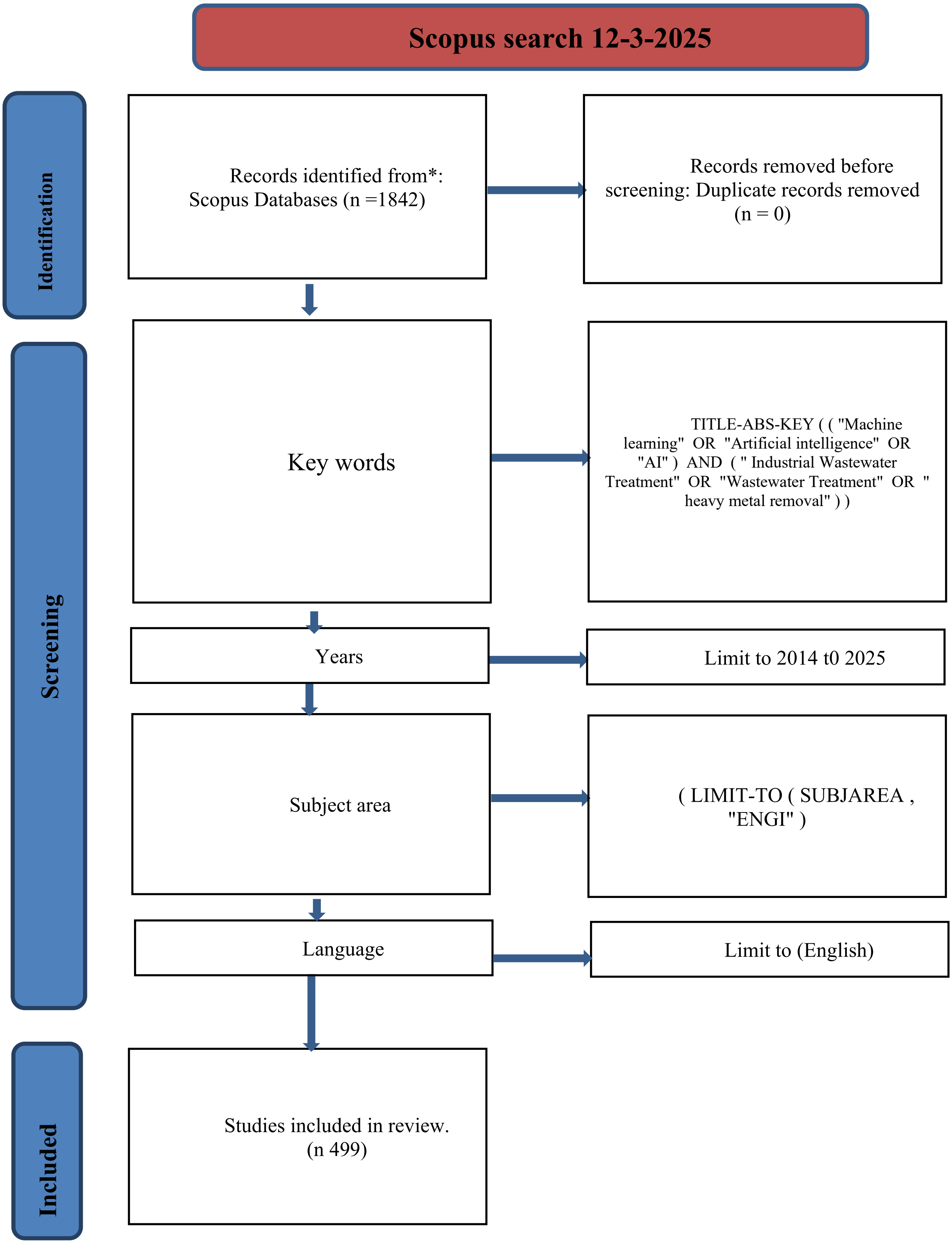

Figure 1: Framework for conducting a bibliometric analysis of machine learning in industrial wastewater treatment.

3.1. Trend of annual publications

1842 documents were initially identified, with 499 aligning with the study's theme. These documents were then categorized as follows: 327 research articles, 51 review papers, 72 conference papers, and 49 documents falling into other categories. The dataset comprises 105 sources and 355 keywords. The publications obtained showed an average growth rate of 37.50% per year. The most notable increase was observed between 2020 and 2024, reaching its peak with 158 publications in 2024, as shown in **Fig. 2**.

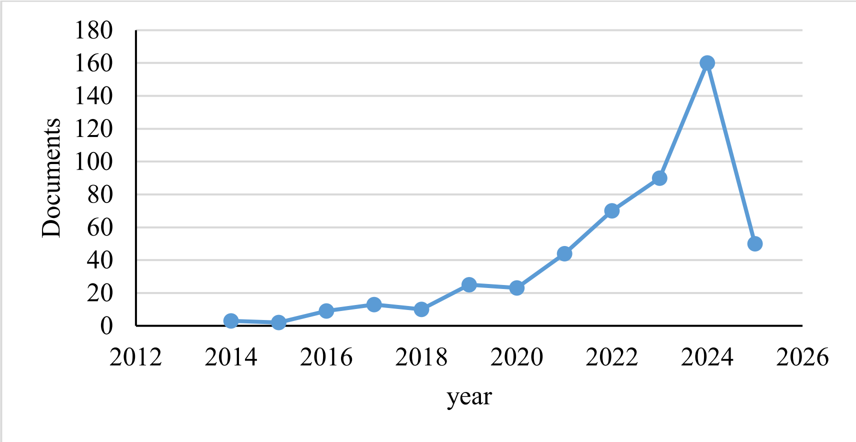

Figure 2: Yearly distributions for machine learning in industrial wastewater treatment.

3.2. Top cited publications of MLin wastewater treatment

The average annual citation was 44.86%, reported in 2024, as illustrated in **Fig. 3**. Only 3027 articles were cited for that particular year. **Fig. 3** illustrates the fluctuation of journals over the years. Until 2024, the journal "Journal Of Water Process Engineering" held the top position, but it was surpassed by the "Water Research," which accumulated a total of 75 articles. In terms of the Cite Score (2023) of journals, the " Water Research " led the rankings with a score of 20.8, followed by " Journal of Cleaner Production " and " Process Safety and Environmental Protection " with scores of 20.4 and 11.4, respectively, as detailed in **Table 1**.

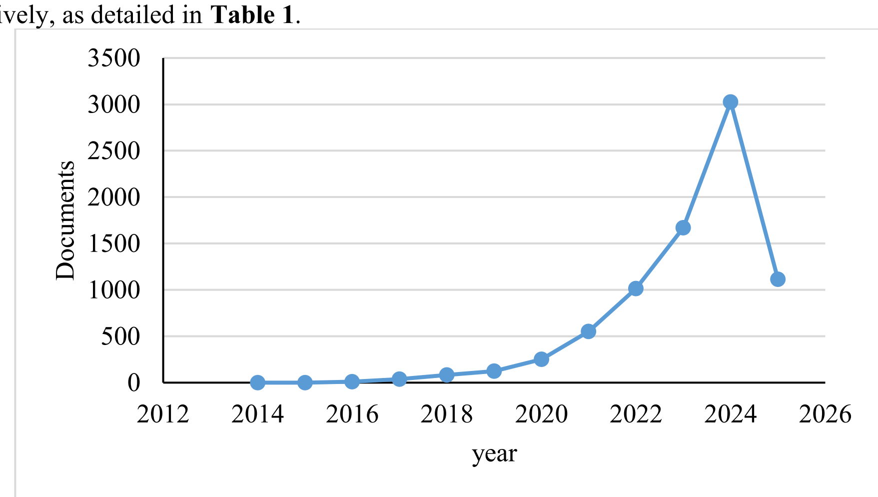

Figure 3: The average yearly citations per article on machine learning in industrial wastewater treatment.

Table 1. The 11 leading journals with the highest productivity in the bibliometric analysis of machine learning for industrial wastewater treatment.

Journal	TP	TC	Cite Score (2023)	Most cited publication	Times Cited	Publisher
Journal of Water Process Engineering	3,477	37,357	10.7	Khan, Mohammad Danish, et al (2023).	163	Elsevier
Water Research	4,826	100,330	20.8	Li, Ning, et al (2023).	163	Elsevier
Desalination and Water Treatment	4,358	9,714	2.2	Xu, Peilong, et al (2023).	55	Elsevier
Journal of Cleaner Production	19,382	394,597	20.4	Mujtaba, Muhammad, et al (2023).	399	Elsevier
Chemical Engineering Journal	-	-	-	Hikita, H., et al (1977).	405	Elsevier
Process Safety and	3,065	34,855	11.4	Aljohani, Meshari M., et al (2023).	168	Institution of Chemical

Environmental Protection						Engineers
Lecture Notes in Networks and Systems	41,485	35,811	0.9	Bavkar, Dnyaneshwar, Ramgopal Kashyap, and Vaishali Khairnar (2023).	115	Springer Nature
Sensors	35,041	256,060	7.3	Wang, Gang, et al (2023).	340	Multidisciplinary Digital Publishing Institute (MDPI)
Lecture Notes in Civil Engineering	17,058	12,939	0.8	Amoura, Nasreddine, et al (2022).	15	Springer Nature
Engineering Applications of Artificial Intelligence	2,673	25,643	9.6	Huynh-The, Thien, et al (2023).	330	Elsevier
Applied Sciences (Switzerland)	44,530	237,130	5.3	Rahman, Md Mostafizer, and Yutaka Watanobe (2023).	424	Multidisciplinary Digital Publishing Institute (MDPI)

TP= Total Publications, TC= Total Citation

3.3. Scientific Fields and Author Metrics

Concerning scientific categories, 33.3% of total articles were categorized under Engineering, followed by Environmental Science and Chemical Engineering with 19.0% and 9.8% of the total articles, respectively as illustrated in **Fig. 4.** The total number of authors across all articles amounted to 159. Notably, “Abba, S.I.” authored the superior number of articles, with 7 articles. Following closely, “Heo, S.K.” , “Szeląg, B.” , and “Yoo, C.K.” contributed 6 articles, while “Nam, K.J.” authored 5 articles as shown in **Fig. 5**. In terms of the authors' H-index, " Wang, A.J." achieved the highest score of 82, followed by " Yaseen, Z.M." with an H-index of 76, and " Ng, H.Y." attained an H-index of 62, as detailed in **Table 2.**

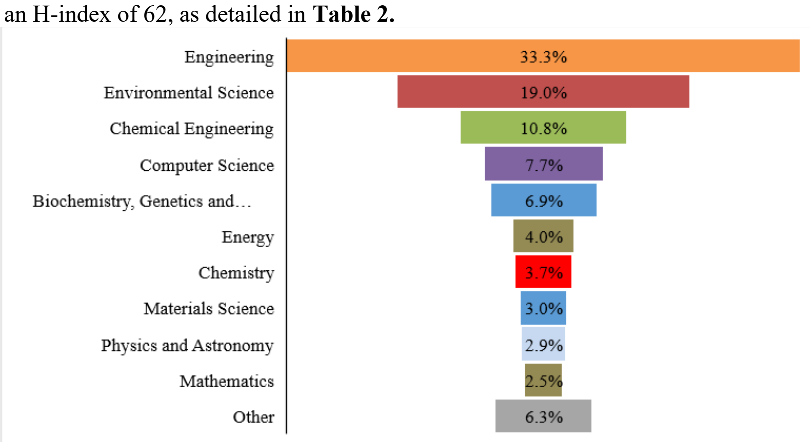

Figure 4: Publications in the research field of machine learning applied to industrial wastewater treatment.

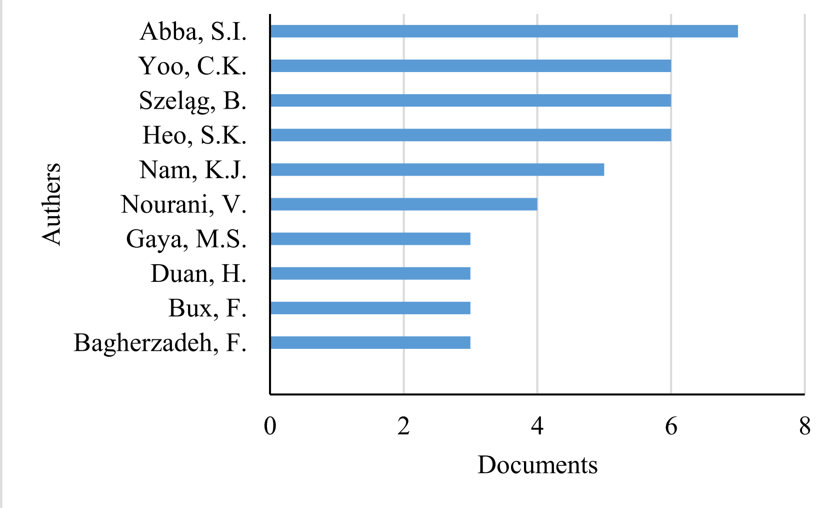

Figure 5: The 10 most prolific authors based on their number of publications on machine learning in industrial wastewater treatment.

Table 2. List of the 30 most prolific authors on machine learning in industrial wastewater treatment.

No	author	TP*	h-index	Current affiliation	Country
1.	Abba, S.I.	210	34	King Fahd University of Petroleum and MineralsThe institution will open in a new tab, Dhahran, Saudi Arabia	Saudi Arabia
2.	Heo, S.K.	57	19	Imperial College LondonThe institution will open in a new tab, London, United Kingdom	United Kingdom
3.	Szeląg, B.	100	14	Politechnika Swietokrzyska w KielcachThe institution will open in a new tab, Kielce, Poland	Poland
4.	Yoo, C.K.	398	51	Kyung Hee UniversityThe institution will open in a new tab, Seoul, South Korea	, South Korea
5.	Nam, K.J.	46	20	Pukyong National UniversityThe institution will open in a new tab, Busan, South Korea	South Korea
6.	Nourani, V.	306	53	University of TabrizThe institution will open in a new tab, Tabriz, Iran	Iran
7.	Bagherzadeh, F.	13	8	Universität BremenThe institution will open in a new tab, Bremen, Germany	Germany
8.	Bux, F.	315	58	Durban University of TechnologyThe institution will open in a new tab, Durban, South Africa	South Africa
9.	Duan, H.	16	10	Harbin Institute of TechnologyThe institution will open in a new tab, Harbin, China	China
10.	Gaya, M.S.	39	11	Kano University of Science and TechnologyThe institution will open in a new tab, Wudil, Nigeria	Nigeria
11.	Hansen, J.	47	10	University of LuxembourgThe institution will open in a new tab, Esch-sur-Alzette, Luxembourg	, Luxembourg
12.	Harrou, F.	210	41	King Abdullah University of Science and TechnologyThe institution will open in a new tab, Thuwal, Saudi Arabia	Saudi Arabia
13.	Hasan, S.W.	254	50	Khalifa University of Science and TechnologyThe institution will open in a new tab, Abu Dhabi, United Arab Emirates	United Arab Emirates
14.	Li, C.	113	33	Harbin Institute of TechnologyThe institution will open in a new tab, Harbin, China	China
15.	Mannina, G.	247	48	Università degli Studi di PalermoThe institution will open in a new tab, Palermo, Italy	Italy
16.	Mehrani, M.J.	19	9	Gdańsk University of TechnologyThe institution will open in a new tab, Gdansk, Poland	, Poland
17.	Mąkinia, J.	134	33	Gdańsk University of TechnologyThe institution will open in a new tab, Gdansk, Poland	Poland
18.	Ng, H.Y.	247	62	Beijing Normal UniversityThe institution will open in a new tab, Beijing, China	China
19.	Qambar, A.S.	3	3	University of BahrainThe institution will open in a new tab, Zallaq, Bahrain	Bahrain

20.	Sun, Y.	273	42	King Abdullah University of Science and TechnologyThe institution will open in a new tab, Thuwal, Saudi Arabia	Saudi Arabia
21.	Torregrossa, D.	15	8	Goodyear S.A.The institution will open in a new tab, Colmarberg, Luxembourg	Luxembourg
22.	Wang, A.J.	824	82	Harbin Institute of TechnologyThe institution will open in a new tab, Harbin, China	China
23.	Wang, H.C.	97	34	Harbin Institute of TechnologyThe institution will open in a new tab, Harbin, China	China
24.	Wang, W.	92	29	Harbin Institute of TechnologyThe institution will open in a new tab, Harbin, China	China
25.	Woo, T.Y.	15	8	Kyung Hee UniversityThe institution will open in a new tab, Seoul, South Korea	South Korea
26.	Yaseen, Z.M.	518	76	King Fahd University of Petroleum and MineralsThe institution will open in a new tab, Dhahran, Saudi Arabia	Saudi Arabia
27.	Zhang, Y.	15	13	Harbin Institute of TechnologyThe institution will open in a new tab, Harbin, China	China
28.	Łagód, G.	178	23	Politechnika LubelskaThe institution will open in a new tab, Lublin, Poland	Poland
29.	Abdulkadir, R.A.	25	12	Kano University of Science and TechnologyThe institution will open in a new tab, Wudil, Nigeria	Nigeria
30.	Afkhamipour, M.	27	14	National Iranian Gas Company (NIGC), Asaluyeh, Iran	Iran

*TP= Total Publications.

3.4. Keyword Frequency and Thematic Categorization of Research Topics

The total number of keywords used in the articles was 355. "Wastewater Treatment" emerged as the most frequently utilized keyword, appearing 351 times, as depicted in **Fig. 6**. This was followed by "Machine Learning" observed 220 times, and "Artificial Intelligence" documented 109 times. As shown in **Table 3**, the frequently occurring keywords in the articles are grouped into six primary subject areas: Wastewater Treatment, Wastewater characteristics, Modeling and Analysis Approaches, Wastewater Treatment Methods, Sustainable and Quality Control, and other related topics. These classifications highlight the most emphasized areas in machine learning in industrial wastewater treatment and the commonly used analytical methods.

Table 3. Grouping of common terms in articles by research domain in machine learning applied to industrial wastewater treatment.

ID	Keywords	Subject Areas	Occurrences
1.	Wastewater Treatment		351
2.	Wastewater		67
3.	Water Quality		65
4.	Reclamation		62
5.	Waste Water Management	Wastewater Treatment	33
6.			
7.	Waste Water		17
8.	Pollutant Removal		16
9.	Wastewater Reclamation		11
10.	Chemical Oxygen Demand		28
11.	Nitrogen		18
12.	Ammonia		18
13.	Dissolved Oxygen	Wastewater characteristics	17
14.	Oxygen		16
15.	Microorganisms		15
16.	PH		14

17.	Heavy Metals		11
18.	Machine Learning	Modeling and Analysis Approaches	220
19.	Artificial Intelligence		109
20.	Machine-learning		104
21.	Forecasting		57
22.	Learning Systems		52
23.	Neural Networks		42
24.	Learning Algorithms		40
25.	Artificial Neural Network		37
26.	Prediction		
27.	Machine Learning Models		31
28.	Deep Learning		31
29.	Decision Trees		26
30.	Random Forest		26
31.	Mean Square Error		
32.	Support Vector Machines		24
33.	Algorithm		
34.	Regression Analysis		17
35.	Biological Water Treatment	Wastewater Treatment Methods	28
36.	Wastewater Treatment Process		21
37.	Procedures		21
38.	Adsorption		20
39.	Oxidation		15
40.	Membranes		12
41.	Anaerobic Digestion		11
42.	Nitrogen Removal		10
43.	Bioreactor		10
44.	Membrane		9
45.	Sustainable Development	Sustainable and Quality Control	25
46.	Quality Control		14
47.	Sustainability		12
48.	Energy Utilization	Other topics	24
49.	Optimization		30
50.	Desalination		9
51.	Health Risks		9

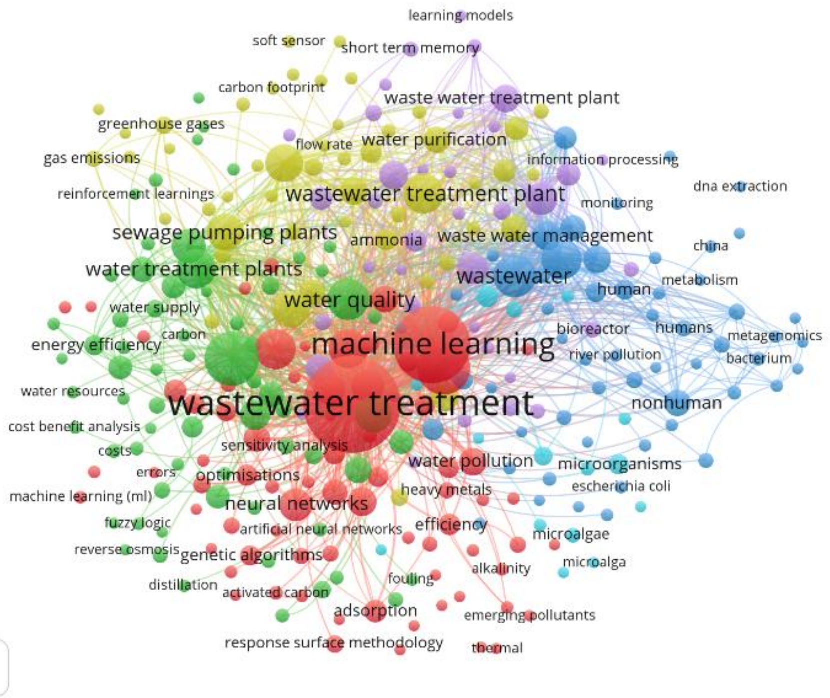

Figure 6: Publications categorized by keywords in machine learning applied to industrial wastewater treatment.

3.5. Top Publishing Countries and Their International Partnerships

The China exhibited the top contributing country, publishing a total of 130 publications, as illustrated in **Fig. 7.** Additionally, it demonstrated robust collaborative connections with other countries, as shown in **Fig. 8.** In second place, India contributed 130 publications, followed by United States ranked third with 64 publications, as detailed in **Table 4.**

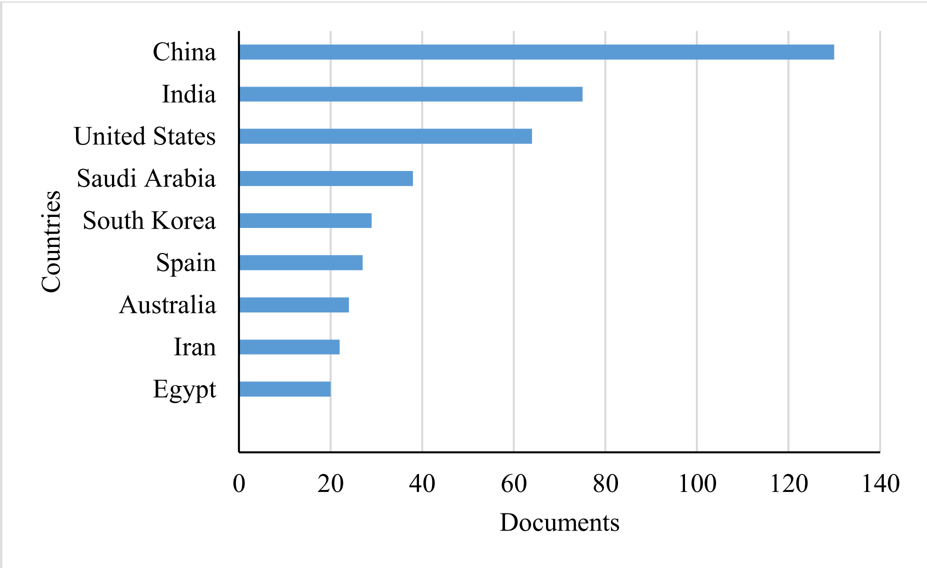

Figure 7: Leading countries in the field of machine learning applied to industrial wastewater treatment.

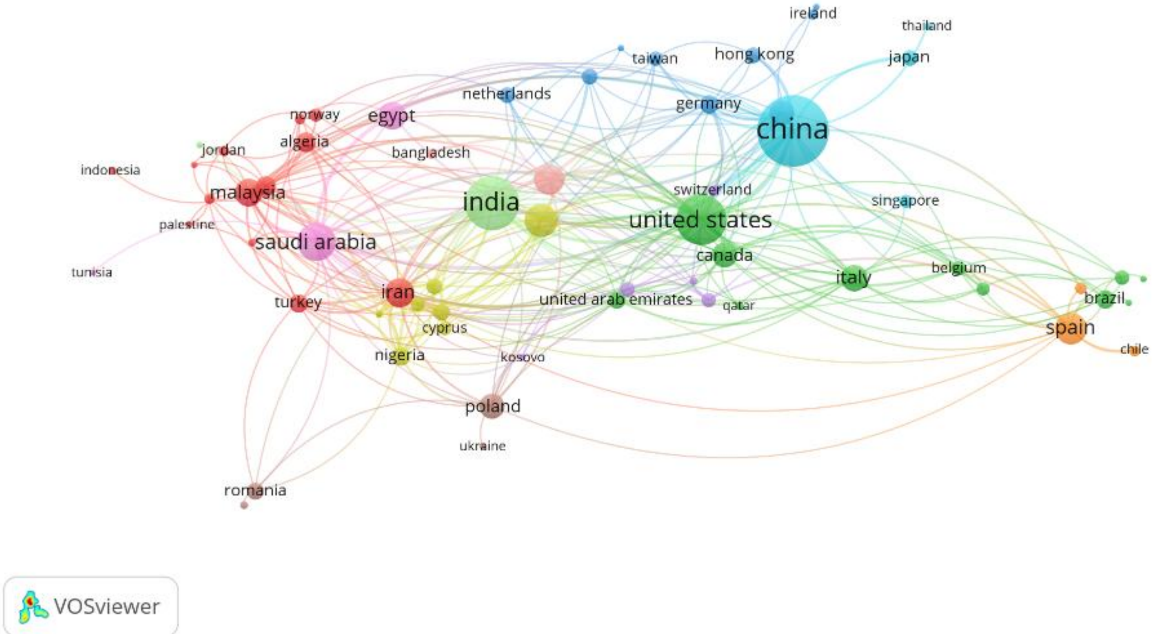

Figure 8: Country co-authorship network in the field of machine learning for industrial wastewater treatment.

Table 4. The most prolific countries in the field of machine learning for industrial wastewater treatment.

COUNTRY	No of articles
China	130
India	75
United States	64
Saudi Arabia	38
South Korea	29
Spain	27

Australia	24
Iran	22
Egypt	20
Malaysia	20
Italy	19
Canada	17
Poland	17
United Kingdom	16
Pakistan	11
Algeria	10
Brazil	9
Germany	9
Nigeria	9
Turkey	9
Greece	8
Romania	8
United Arab Emirates	8
Hong Kong	7
Japan	7
Netherlands	7
South Africa	7
Viet Nam	7
Belgium	6
France	6

3.6. Top Research Affiliations in Machine Learning for Wastewater Treatment

The most productive affiliation was “Ministry of Education of the People's Republic of China” with 16 articles, followed by “Harbin Institute of Technology” with 15 articles and “Chinese Academy of Sciences” with 11 articles as shown in **Fig. 9**.

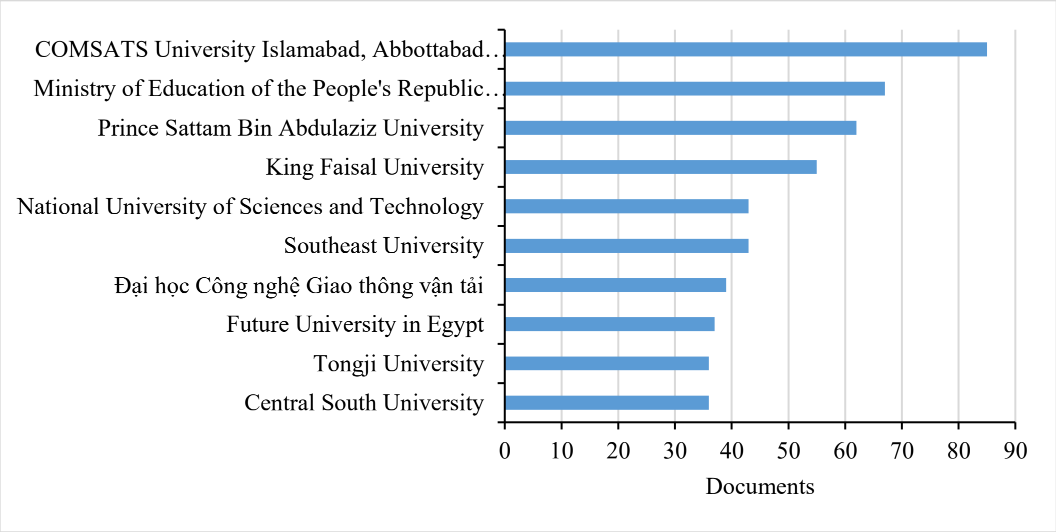

Figure 9: The 10 leading affiliations ranked by the number of publications in the field of machine learning for industrial wastewater treatment.

4. Discussion

Industrial wastewater treatment is critical for environmental sustainability and public health. With the increasing complexity of industrial effluents and stringent regulatory standards, machine learning (ML) has emerged as a transformative tool in optimizing treatment processes. Understanding the factors influencing wastewater treatment efficiency, such as pollutant characteristics, treatment methodologies, environmental conditions, and operational parameters, is essential for advancing research and practical applications(Agustiono et al., 2024; Baarimah et al., 2024; De la Hoz-M et al., 2024; Singh et al., 2023).

The effectiveness of wastewater treatment is highly dependent on various material and process-related factors, including the composition of industrial effluents, chemical additives, microbial activity, treatment duration, and environmental variables such as temperature and pH(Aprianti et al., 2019; Emamgholiloo et al., 2024; Ramya et al., 2022; Tu et al., 2021; Y. Wang et al., 2024). The interaction between these factors determines the efficiency of pollutant removal, making predictive modeling a crucial aspect of improving treatment outcomes. Traditional treatment systems rely on empirical models and manual optimization, but ML techniques have introduced new possibilities for predictive analytics and process control(Iloms et al., 2020; Kwiatkowska & Ormaniec, 2024; Mutegoa, 2024; Oladimeji et al., 2024).

This study analyzes global research trends in applying ML to industrial wastewater treatment through bibliometric methods using VOSviewer. Of the 499 research articles published between 2014 and March 12, 2025, a significant proportion originated from China, India, the United States, Saudi Arabia, and South Korea, reflecting these countries' strong industrial bases, regulatory emphasis, and research investments in sustainable wastewater management.

The bibliometric analysis highlights six major areas of study: Wastewater Treatment, Wastewater characteristics, Modeling and Analysis Approaches, Wastewater Treatment Methods, Sustainable and Quality Control, and other related topics. Each of these domains contributes to the advancement of wastewater treatment by improving efficiency, reducing costs, and minimizing environmental impacts. In treatment optimization, examining the influence of various operational parameters, microbial communities, and chemical interactions is critical. The development of advanced treatment techniques, such as membrane bioreactors and electrocoagulation, further enhances industrial wastewater management.

Traditional wastewater treatment studies rely on physicochemical and biological parameters as input variables, with pollutant removal efficiency as the output as shown in **Fig.10**. However, ML-driven approaches introduce more complex input-output relationships, allowing for more accurate predictions and real-time decision-making. Several ML techniques are widely used in wastewater treatment, including Multiple Linear Regression (MLR), Random Forest (RF), Support Vector Regression (SVR), Decision Tree (DT), Gradient Boosting Regression (GBR), Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Gene Expression Programming (GEP)(Alprol et al., 2024; Alvi et al., 2023; Cairone et al., 2024; Duarte et al., 2024; Engineering, 2024; Ganthavee & Trzcinski, 2024; Gomaa, Lotfy, et al., 2024; Jafar et al., 2022). Each of these techniques has distinct advantages and limitations:

- MLR effectively models linear relationships but struggles with nonlinear interactions.
- RF enhances predictive accuracy by training multiple decision trees but demands significant computational power.
- SVR captures nonlinear patterns but lacks interpretability, making process optimization challenging.
- DT simplifies rule-based modeling but may overfit when handling complex datasets.
- GBR improves accuracy by sequentially training decision trees but is computationally intensive.
- ANN excels in modeling nonlinear relationships but requires large datasets and is prone to overfitting.
- ANFIS combines neural networks with fuzzy logic, providing hybrid solutions but requiring substantial processing power.
- GEP efficiently models complex wastewater treatment processes but necessitates careful parameter tuning for optimal results.

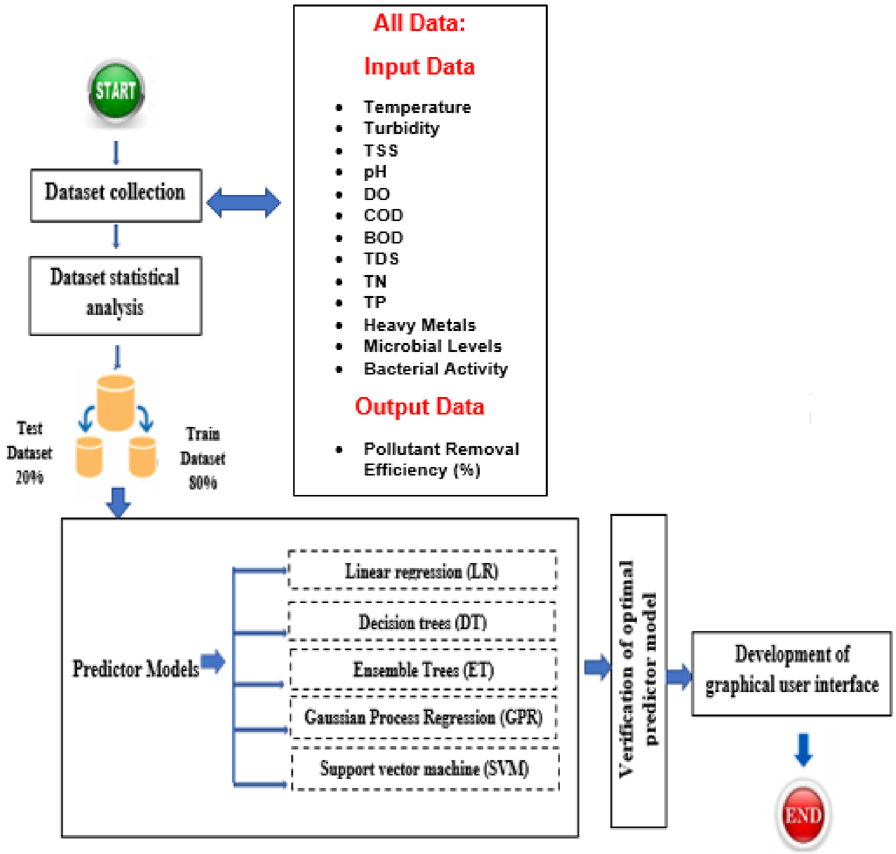

Figure 10: Flow-work diagram for predicting the pollutant removal efficiency (%).

The study underscores the importance of large, diverse datasets for improving ML model accuracy in wastewater treatment. Future research should focus on enhancing dataset availability, increasing model interpretability, and integrating real-time monitoring with predictive analytics. Innovations such as smart sensors, IoT-enabled treatment plants, and AI-driven automation will likely shape the future of industrial wastewater management. These advancements will aid industries, policymakers, and researchers in making informed decisions regarding sustainable treatment practices, regulatory compliance, and resource optimization.

By leveraging ML methodologies, industrial wastewater treatment can become more efficient, cost-effective, and sustainable. Future advancements in AI, automation, and data analytics will further enhance treatment processes, contributing to a cleaner and more sustainable industrial ecosystem.

5. Qualitative Synthesis of Machine Learning Applications in Wastewater Treatment

While the bibliometric trends reveal the growth and distribution of research in machine learning (ML) applications for wastewater treatment, a nuanced understanding of how these techniques are applied in practice and their respective strengths and weaknesses is crucial for interpreting the scientific value and practical significance of this research domain.

5.1. Core Application Areas

5.1.1. Prediction and Forecasting

One of the most prevalent applications of machine learning in wastewater treatment is the prediction of effluent quality parameters, including chemical oxygen demand (COD), biological oxygen demand (BOD), total suspended solids (TSS), nitrogen species (e.g., NH_3 and NO_3^-), and phosphorus concentrations. Supervised learning models particularly Artificial Neural Networks (ANNs), Support Vector Regression (SVR), and Random Forest Regression (RFR) have demonstrated high predictive accuracy, owing to their ability to capture complex, nonlinear relationships within process data. ANNs are especially effective in modeling dynamic systems with multiple inputs and outputs, although they require extensive datasets and careful parameter tuning to perform optimally. SVR, on the other hand, is valued for its robustness in high-dimensional spaces and its strong generalization capability, especially with small to medium-sized datasets. Additionally, ensemble learning models such as Gradient Boosting Machines (GBM) and XGBoost are increasingly being adopted, as they offer enhanced predictive performance and greater resistance to overfitting, making them suitable for a wide range of wastewater treatment scenarios.

5.1.2. Process Control and Optimization

Machine learning is also increasingly utilized for real-time process optimization in advanced wastewater treatment systems such as activated sludge processes, sequencing batch reactors (SBRs), and membrane bioreactors (MBRs). By integrating machine learning with reinforcement learning (RL) and model predictive control (MPC) frameworks, adaptive control strategies can be developed to regulate key operational parameters, including aeration rates, chemical dosing, and sludge retention time. These intelligent control systems contribute to significant reductions in operational costs while ensuring compliance with environmental discharge standards. For instance, hybrid ANN-MPC models have demonstrated the potential to reduce aeration energy consumption by up to 30%, without compromising effluent quality. Moreover, the incorporation of fuzzy logic and genetic algorithms alongside ML techniques allows for more robust handling of system uncertainties and facilitates the optimization of complex, multi-objective problems in wastewater treatment operations.

5.1.3. Fault Detection and Anomaly Diagnosis

Unsupervised learning techniques, including k-means clustering, autoencoders, and principal component analysis (PCA), are widely applied in wastewater treatment for tasks such as fault detection, sensor drift identification, and the development of early warning systems. These methods analyze historical or real-time process data to uncover patterns and detect anomalies without the need for labeled datasets. By identifying deviations from normal operating conditions, they enable proactive maintenance and system reliability. For example, autoencoder-based deep learning frameworks have demonstrated strong performance in detecting anomalies within real-time SCADA (Supervisory Control and Data Acquisition) data, achieving high detection accuracy with minimal false alarms. This enhances operational safety, supports timely intervention, and contributes to the overall robustness of wastewater treatment facilities.

5.2. Strengths of ML in Wastewater Applications

Machine learning offers significant advantages in the field of wastewater treatment due to its high flexibility and scalability. ML models can be tailored to suit a wide range of treatment processes and operational scales, from pilot-scale experiments to full-scale industrial plants. This adaptability makes ML a valuable tool across diverse treatment configurations and contexts. Furthermore, ML facilitates improved decision-making by generating data-driven insights that reduce dependence on traditional empirical approaches and trial-and-error methods, thereby enhancing overall process understanding and operational efficiency. Additionally, the integration of ML with smart infrastructure supports the development of intelligent decision support systems and digital twins for water utilities, paving the way for more efficient, responsive, and sustainable water management practices.

5.3. Challenges and Limitations

Despite the promising capabilities of machine learning in wastewater treatment, several limitations continue to impede its widespread, full-scale deployment. One of the primary challenges lies in data quality and availability. Many treatment facilities lack high-resolution, continuous datasets, and issues such as sensor malfunctions, missing data, and inconsistent sampling frequencies introduce significant complexities in data preprocessing. Another critical concern is model interpretability. Advanced techniques like deep neural networks often function as "black-box" models, which can hinder their acceptance among engineers, operators, and regulatory bodies due to the lack of transparent decision-making processes. Additionally, the generalizability of ML models remains limited, as site-specific models frequently fail to perform accurately when applied to systems with different influent characteristics or operational conditions. Emerging approaches such as transfer learning and domain adaptation aim to mitigate this issue. Lastly, the computational demands of real-time ML applications can be substantial, particularly when processing streaming data or managing large-scale systems, thereby necessitating access to high-performance computing resources.

5.4. Emerging Directions

The future of machine learning in wastewater treatment is increasingly oriented toward hybrid modeling approaches, which integrate data-driven ML algorithms with traditional mechanistic process models to enhance both predictive accuracy and interpretability. This synergistic modeling strategy enables a deeper understanding of system dynamics while retaining the adaptability of machine learning. Additionally, the convergence of ML with emerging technologies such as edge computing, the Internet of Things (IoT), and cloud-based platforms is paving the way for real-time monitoring, predictive maintenance, and the development of decentralized treatment systems. These integrations support more responsive and efficient wastewater management. Furthermore, advanced ML architectures—including transformer models, graph neural networks (GNNs) for spatial data analysis, and physics-informed neural networks (PINNs)—are gaining traction as they offer more robust, transparent, and physically consistent modeling frameworks suitable for complex environmental systems.

6. Implications for Practice

The findings of this bibliometric and qualitative analysis offer several actionable insights for the application of machine learning (ML) in real-world wastewater treatment systems. While the academic literature is rapidly expanding, there remains a critical need to bridge the gap between research and operational implementation.

6.1. Guidance for Technology Adoption

This study identifies that machine learning techniques such as artificial neural networks (ANNs), support vector machines (SVMs), and random forests (RF) are among the most frequently applied models for tasks including effluent quality prediction, energy optimization, and process control. These methods have demonstrated potential to enhance predictive accuracy and operational efficiency when integrated into supervisory control systems at treatment plants.

6.2. Supporting Real-Time Monitoring and Decision-Making

The increasing use of ML for real-time data analysis and anomaly detection indicates a shift towards smart wastewater management. Treatment plant operators can leverage such tools to automate monitoring, reduce manual sampling, and detect system failures or inefficiencies early leading to more proactive and cost-effective operations.

6.3. Addressing Practical Limitations

Despite the advantages of machine learning in wastewater treatment, several practical challenges continue to hinder its widespread implementation. A significant number of studies are based on laboratory-scale experiments or simulation data, which often fail to capture the variability and operational complexity of full-scale treatment facilities. Furthermore, the absence of standardized datasets and limited access to high-quality, real-time operational data restrict the generalizability and scalability of developed models. Another major concern is the interpretability of ML models, as many advanced algorithms function as "black boxes," making it difficult for operators to trust and act on their outputs without clear, transparent reasoning. These challenges highlight the need for future research to prioritize collaborative pilot projects that involve both researchers and wastewater utility operators. Such initiatives can help validate machine learning solutions under real-world conditions, bridge the gap between academic innovation and practical application, and foster greater confidence in ML-based decision support systems.

6.4. Policy and Strategic Implications

The bibliometric analysis also reveals global disparities in research contributions. Practitioners in developing regions may benefit from knowledge transfer initiatives and international partnerships to facilitate the deployment of ML technologies.

6.5. Path Forward

To fully harness the potential of machine learning in wastewater treatment, several strategic actions are essential. First, substantial investments in digital infrastructure such as advanced sensors, automated monitoring systems, and robust data management platforms are required to support real-time data acquisition and analysis. Second, the development of ML models must account for practical operational constraints and human factors to ensure usability, reliability, and acceptance by plant operators and decision-makers. Finally, effective implementation demands cross-disciplinary collaboration among engineers, data scientists, environmental specialists, and regulatory authorities. Such integrative efforts are critical to designing solutions that are not only technically sound but also aligned with regulatory frameworks and practical operational needs.

7. Conclusion

This study has provided a comprehensive bibliometric analysis of research trends in applying machine learning (ML) to industrial wastewater treatment. By examining key publications, citation patterns, and influential contributors, we have identified the growing role of ML in optimizing treatment processes, predicting contaminant behavior, and improving operational efficiency. The findings underscore the increasing adoption of ML techniques such as artificial neural networks (ANN), support vector machines (SVM), and deep learning for contaminant removal, process optimization, and real-time monitoring. While ML has demonstrated significant potential in revolutionizing industrial wastewater treatment, challenges such as data availability, model interpretability, and regulatory compliance remain. Addressing these issues will be critical for the broader adoption of ML-driven solutions in this field.

7.1. Study Contributions

This study contributes to the field of industrial wastewater treatment by mapping the research landscape and highlighting key advancements in ML applications. The bibliometric approach used in this analysis provides a structured view of the evolution of research in this domain, identifying prominent researchers, institutions, and influential studies. Additionally, the categorization of research themes into wastewater treatment methods, modeling approaches, and sustainability practices offers valuable insights for future research directions. By synthesizing information from a wide range of sources, this study bridges gaps in the literature and emphasizes the importance of interdisciplinary collaboration between environmental engineering and artificial intelligence (AI) fields.

7.2. Suggestions for Academia and Industry Practice

For academia, future research should focus on developing robust ML models that enhance predictive accuracy and adaptability to real-world wastewater treatment scenarios. More emphasis should be placed on hybrid ML models that combine traditional statistical methods with AI-driven techniques. Researchers should also work on expanding publicly available datasets to improve model training and validation processes. Additionally, further studies are needed to assess the ethical, regulatory, and environmental implications of AI-driven wastewater treatment systems.

For industry practice, wastewater treatment facilities should explore integrating ML-based predictive analytics to improve operational efficiency and resource allocation. Investment in smart sensors and IoT-enabled monitoring systems can enhance data collection, allowing for more accurate ML-driven predictions and automated decision-making. Collaboration between AI developers and wastewater treatment engineers is essential to ensure practical implementation of ML solutions that align with industry requirements and environmental regulations.

7.3. Limitations of This Study

While this study provides a comprehensive bibliometric analysis, it has several limitations. First, the study relies primarily on publications indexed in the Scopus database, which may exclude relevant research from other databases such as Web of Science or Google Scholar. Second, bibliometric analysis focuses on quantitative trends rather than qualitative assessments of study methodologies, which may limit the depth of insights into specific ML techniques. Additionally, the study does not address potential biases in citation patterns, such as self-citation or publication accessibility disparities across regions. Future research should incorporate a more diverse range of data sources and methodologies to provide a more holistic understanding of ML applications in industrial wastewater treatment.

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