Modeling the Barriers to Implementing Artificial Intelligence in Desalination Supply Chain Using MICMAC

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ABSTRACT

This study examined the barriers to adopting Artificial Intelligence (AI) in desalination supply chain (SC), a sector increasingly seen as vital for tackling global water scarcity. Despite AI's proven ability to improve efficiency, sustainability, and decision-making in complex supply chains, its implementation in desalination systems encounters formidable challenges. Through a comprehensive literature review and expert consultations, sixteen barriers were identified and analyzed structurally using the MICMAC approach. The results showed that four factors are the most influential barriers and serve as bottlenecks for successful AI adoption: lack of funding and capital, lack of standardization and interoperability, shortage of specific skills and talent, and data privacy and security concerns. The present study emphasizes the need for integrated strategies that include financial support, common standards, skill development programs, and strong data protection frameworks. It also highlights the importance of collaboration among governments, private sector stakeholders, and research institutions to overcome systemic obstacles. The findings may not only offer insights into the key drivers of AI implementation in desalination but also provide a roadmap for policymakers and industry leaders aiming to develop more resilient and sustainable water management systems.

KEYWORDS

Artificial Intelligence (AI), desalination supply chain, MICMAC analysis, structural analysis, supply chain management.

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Introduction

The increasing global population, rapid urbanization, and industrial growth have greatly increased the demand for fresh water, making desalination an essential and viable solution to address water scarcity from abundant but salty sources like seawater and brackish water (Ali et al., 2024; Balaji et al., 2021; Fares et al., 2019; Hanasaki et al., 2016; Ignatov et al., 2024; Jeong et al., 2024; Kocher & Menon, 2023; Ozaveshe et al., 2023; Sabet et al., 2019; Salman & Aswad, 2022; Velmurugan et al., 2020). This process is deemed critical for water supply and management, especially in coastal areas, where coastal reservoirs may also need desalting before using (Balaji et al., 2021). However, desalination is naturally an energy-sapping process, with most existing facilities historically relying on fossil fuels, which raises serious concerns about fluctuating prices, limited resources, and negative environmental impacts like pollutant emissions and greenhouse gases (Abdulrahim & Ahmed, 2022; Alqaed et al., 2021; Imandoust et al., 2025; Rau & Naas, 2024; Ritika et al., 2023; Shokri & Fard, 2022; Wang et al., 2020). Additionally, the industry faces ongoing issues related to managing concentrated brine discharge and maintaining environmental sustainability, requiring a comprehensive approach to optimize operations and reduce ecological footprints (Charcosset, 2022; Park & Lee, 2022).

To improve the efficiency, sustainability, and cost-effectiveness of desalination processes, advanced technologies, including AI, show great promise. AI has made significant progress in various industrial fields, offering capabilities for optimization, predictive analysis, and complex system management (Bakas & Kontoleon, 2023; Bhatt et al., 2024; Gao et al., 2023; Gosai, 2023; Hayot et al., 2024; Jain, 2024; Maier et al., 2024; Masod & Zakaria, 2024; Mypati et al., 2023; Orejuela-Escobar et al., 2024; Peckham et al., 2025; Rathee et al., 2023; Tolk, 2024). Because the desalination supply chain (SC) is complex, covering everything from raw water intake and energy supply to treatment and distribution, AI could potentially enhance operations by optimizing energy use, increasing efficiency, and supporting better decision-making across the entire process (Abaku et al., 2024; Choudhuri, 2024; Dhal & Kar, 2024; Ejjami & Boussalham, 2024; Gomes et al., 2024; Hasan et al., 2024; Ike et al., 2024; Joel et al., 2024). Specifically, AI-based process design, optimization, and control are key tools to address the complexity of desalination technologies, including hybrid systems, and can provide a comprehensive understanding of challenges where traditional experimental and theoretical methods fall short (Son et al., 2022). AI algorithms, such as machine learning and artificial neural networks, lead the way in advancing AI-supported smart desalination (Son et al., 2022).

Despite the significant potential mentioned above, successfully integrating and widely adopting AI within desalination SC faces several challenges. Although AI is rapidly advancing in many areas, its application in complex industrial management contexts like desalination industry may encounter unique technical, operational, economic, and organizational hurdles (Ijiga et al., 2024; Jain, 2024; Kelly, 2024; Louis & Eyo-Udo, 2024;

Nendrambaka, 2024; Ola et al., 2024; Riad et al., 2024). These barriers include the need for high-quality data, algorithmic complexity, integration difficulties, substantial initial infrastructure investments, concerns about data quality, workforce adaptation requirements, high implementation costs, skills shortages, and regulatory challenges (Ike et al., 2024; Jain, 2024; Kelly, 2024; Li, 2024; Louis & Eyo-Udo, 2024; Maier et al., 2024; Masod & Zakaria, 2024; Nendrambaka, 2024; Ola et al., 2024; Peckham et al., 2025; Riad et al., 2024). Understanding and systematically addressing these barriers are essential for unlocking AI's full potential to optimize water production, reduce energy consumption, minimize environmental impacts, and support more sustainable and efficient water resource management globally (Ejjami & Boussalham, 2024; Joel et al., 2024; Kelly, 2024; Louis & Eyo-Udo, 2024; Riad et al., 2024). Therefore, this research aimed to identify and analyze the key barriers to AI integration in desalination SC, providing insights to facilitate its effective adoption and help create a more resilient and sustainable water future. This study has attempted to address the following questions: What are the main barriers to implementing AI in desalination SC? How can these barriers be structured based on their driving and dependence power using MICMAC analysis?

Literature Review

Toorajipour et al. (2021) conducted a systematic literature review to examine the contributions of AI in supply chain management (SCM). Their study highlighted the most prevalent AI techniques currently employed in SCM, as well as potential AI applications that could further enhance both research and practice. The review identified several subfields where AI has already improved operations, such as logistics, marketing, and production, while also pointing out areas with high potential for future AI integration. Despite these benefits, challenges were also noted, including the need for more comprehensive empirical studies, data quality concerns, and the adaptation of AI methods to specific industrial contexts. The authors suggested that addressing these gaps through targeted research, technological development, and workforce training could facilitate more effective AI adoption in SC operations. Earlier studies also recognized the importance of AI in SC optimization, highlighting initial barriers and opportunities (Hanasaki et al., 2016; Rahman et al., 2020; Velmurugan et al., 2020). Fathi et al. (2025) identified and ranked barriers to IoT implementation in the food SC. Rostami et al. (2025) comparatively analyzed and assessed risk dynamics across diverse global markets by using machine learning. Elyaakouby and Tilioua (2025) reviewed the integration of AI in water treatment, particularly through reverse osmosis (RO) processes. Their study emphasized the benefits of AI technologies, especially machine learning algorithms, in enhancing operational efficiency, reducing energy consumption, and optimizing system performance. AI applications in RO processes include predicting and managing membrane fouling, dynamically adjusting pump operations and pressure settings, and performing real-time monitoring and anomaly detection. These capabilities enable proactive maintenance, reduce downtime, and ensure consistent water quality. Case studies highlighted practical advantages such as lower maintenance costs, improved resource utilization, and more sustainable water management. The authors suggested that addressing technical and operational challenges through AI can significantly contribute to the effectiveness and resilience of desalination supply chains. In another study, Chekifi et al. (2024) examined the integration of renewable energy sources, such as solar, wind, and geothermal, with desalination technologies, emphasizing the opportunities and challenges of powering desalination plants in remote regions. While renewable-powered systems can be reliable and cost-effective, their intermittent nature complicates system design. The study highlighted the role of AI in addressing these challenges, including forecasting energy availability, optimizing operational parameters, and enhancing control systems for improved efficiency and sustainability. AI-driven solutions were shown to facilitate better system performance, enabling dynamic adjustments to variable energy inputs, and supporting more resilient and sustainable desalination operations. The evidence from this study suggested that leveraging AI in renewable-powered desalination can significantly enhance water production efficiency and promote sustainable water management practices. Krishnan et al. (2024) explored the integration of AI with nanomembrane systems for advanced water desalination. Their study highlighted how AI, through machine learning and neural networks, enhances real-time monitoring, adaptive responses, and proactive maintenance of nanomembranes, optimizing energy consumption, mitigating membrane fouling, and extending membrane lifespan. These AI-enhanced systems continuously learn and improve under varying operational conditions, supporting decentralized water solutions and enabling remote management in areas with limited access to clean water. Despite the substantial potential, challenges have also remained, including the development of desalination-specific AI algorithms, ensuring scalability and compatibility, and addressing data privacy and security issues. The authors suggested that ongoing research and innovative design efforts are crucial for fully leveraging AI-driven nanomembrane technologies to improve the efficiency, sustainability, and accessibility of water desalination processes. Abba et al. (2023) investigated the integration of AI with hybrid nanofiltration/reverse osmosis (NF–RO) desalination plants using a deep learning-based Crow Search Optimization Algorithm (LSTM-CSA). Their study demonstrated how AI models can optimize the performance of NF–RO processes by accurately predicting permeate conductivity, evaluating uncertainties via Monte Carlo simulations, and applying statistical performance metrics such as RMSE and MAE. The LSTM-CSA model outperformed conventional LSTM, achieving higher predictive accuracy and enabling advanced energy optimization, improved operational strategies, and sustainable brine management. The authors emphasized AI's role in facilitating resource recovery from brine, minimizing waste, and supporting sustainable and resilient water desalination operations. Drogkoula et al. (2023) provided a comprehensive survey of machine learning (ML) methodologies with a focus on their applications in water resources management. The study highlighted how AI and ML can increase sustainability and efficiency in managing environmental challenges, including climate change and ecosystem degradation. This study investigated the application of AI in irrigation optimization, water quality assessment, flood prediction, and water demand forecasting through the analysis of heterogeneous data sources, including remote sensing, smart sensor networks, and social media platforms. The authors emphasized the benefits of AI-driven integration and decision support in water management, including improvements in agricultural practices, water distribution, and desalination plant operations. Challenges related to data heterogeneity, stakeholder education, and implementation costs were also discussed, pointing to areas requiring further research to enable broader adoption of AI solutions in water resources management. Mahadeva et al. (2023) investigated the application of AI in water desalination, highlighting its potential for promoting global sustainability. The study emphasized that AI techniques, including artificial neural networks (ANN), genetic algorithms (GA), fuzzy logic, and swarm optimization methods, have been increasingly employed since 2010 to optimize desalination processes. These approaches enhance both water quality and quantity while enabling real-time process optimization and automation. The authors argued that integrating AI into desalination operations can significantly improve water resource management, system efficiency, and sustainability, particularly in the face of climate variability and growing global water demand. Finally, Modgil et al. (2022) explored the role of AI in enhancing SC resilience, particularly in response to disruptions caused by the COVID-19 pandemic. Drawing on semi-structured interviews with 35 e-commerce SC experts, the study identified five principal domains in which AI enhances resilience: enhancing transparency, facilitating last-mile delivery, delivering personalized solutions for both upstream and downstream stakeholders, mitigating the effects of disruptions, and enabling agile procurement strategies. The authors emphasized that AI-enabled dynamic capabilities help firms develop business continuity mechanisms and bridge the gap between theory and practice, demonstrating how AI can strengthen supply chains against future risks.

Methodology

This study was designed to identify the barriers to implementing AI in desalination SC and to analyze their structural relationships using the MICMAC approach. Initially, a comprehensive literature review was conducted to extract a preliminary list of potential barriers. In this stage, reputable scientific databases such as Scopus and Web of Science were searched using keywords related to AI, SCM, and implementation challenges. Some research articles reviewed the databases and papers manually in the past (Farazmand, 2019) or recently via the bibliometric approach (Nourahmadi, 2025; Nourahmadi, 2021; Rasti, 2024). The initial list of barriers was then reviewed and refined through expert consultation, involving engineers and managers with at least five years of experience in AI and desalination projects, ensuring that the identified barriers were both comprehensive and relevant.

The MICMAC (Matrice d'Impacts Croisés Multiplication Appliquée à un Classement) method is a structural analysis technique used to identify and classify factors based on their driving power and dependence power. In this study, after experts evaluated the barriers using pairwise comparisons, the data were entered into the MICMAC software. The software calculated direct and indirect influences among variables and generated an influence-dependence map, which helps categorize barriers into four quadrants: autonomous, dependent, linkage, and driving factors. This process enables researchers to prioritize barriers and understand their interrelationships systematically.

Next, the MICMAC structural analysis method was utilized to examine the causal relationships and interdependencies among the barriers. A total of 20 experts with professional and academic experience in the relevant fields participated in assessing the relationships among the barriers through pairwise comparison matrices. The collected data were painstakingly analyzed using MICMAC software to determine the driving and dependent power of each barrier, thereby identifying the key factors that influence successful AI implementation in desalination SC. This combined approach provides a structured and comprehensive view of the barriers and their interrelationships, offering practical guidance for decision-making in this field.

Analysis and Results

The barriers to the implementation of AI in desalination SC were systematically identified through an extensive review of the literature complemented by consultations with domain experts. A thorough list of these barriers is presented in Table 1.

Following the identification of 16 barriers through an extensive literature review and consultations with 20 domain experts, the barriers were incorporated into an expert evaluation questionnaire. The experts were asked to assess the importance of each barrier on a five-point Likert scale. A total of 20 completed questionnaires were analyzed using SPSS, and all 16 barriers were validated at a significance level of 0.05, confirming their relevance based on expert judgment. After finalizing the key barriers to the implementation of AI in desalination SC, these barriers were incorporated into the cross-impact analysis matrix. A standardized cross-impact questionnaire was then developed and distributed to the experts. The average of the collected responses was subsequently used as the input for the MICMAC software, as summarized in Figure 1.

Table 1.
The Identified Barriers to AI Implementation in Desalination (SC)

Barrier Category	Barrier	Description of Barrier	Source
Financial	High Implementation and Running Costs	The significant upfront investment required for AI technologies, including hardware, software, and infrastructure, can be a major deterrent. This also includes difficulties in demonstrating a clear return on investment (ROI) or building a compelling business case for AI projects.	Adesoga et al., 2024; Agrawal et al., 2019; Ardiantono et al., 2024; Balon et al., 2024; Cannas et al., 2023; Gonçalves et al., 2024; Hangl et al., 2022; Heeres et al., 2023; Nitsche et al., 2023; Nyamekeh et al., 2025; Oyedijo et al., 2023; Rijanto, 2024; Thakker et al., 2024; Yazdi et al., 2022
	Lack of Funding and Capital	Insufficient financial resources within an organization or a sector to invest in new AI initiatives will cause concern.	Gonçalves et al., 2024
	Poor Cash Flow Management	Inefficient management of financial flows and working capital can hinder the ability to fund and sustain AI projects.	Sahoo & Thakur, 2022

Barrier Category	Barrier	Description of Barrier	Source
Technological	Data Quality and Integration Issues	AI systems heavily rely on high-quality, consistent, and integrated data. Challenges include poor data quality, disparate data sources, and the complexity of integrating new AI systems with existing legacy infrastructure.	Adeniran et al., 2024; Adesoga et al., 2024; Cannas et al., 2023; Husein et al., 2024; Khlie et al., 2024; Nyamekeh et al., 2025; Shrivastav, 2022
	Lack of Standardization and Interoperability	The absence of common standards for AI technologies and data formats can make it difficult for different systems and partners within the SC to communicate and collaborate effectively.	Bag et al., 2023; Nitsche et al., 2023
	Insufficient Technological Maturity	Some AI technologies may still be in early stages of development, lacking the robustness, reliability, or proven track record for widespread industrial application.	Nitsche et al., 2023
	Data Privacy and Security Concerns	The collection and processing of large volumes of sensitive data by AI systems raise significant concerns about privacy breaches, cybersecurity risks, and compliance with data protection regulations.	Adesoga et al., 2024; Ijiga et al., 2024; Ismaeil & Lalla, 2024; Kramer, 2024; Nyamekeh et al., 2025
	Algorithmic Transparency and Explainability	The opaque or 'black box' nature of certain AI algorithms often obscures the decision-making process, thereby raising concerns related to trust, accountability, and adherence to regulatory standards.	Ijiga et al., 2024
	Scalability Issues	There are challenges in scaling AI solutions to meet the demands of large and complex SC operations.	Rijanto, 2024; Shankaran, 2024
Organizational & Human	Resistance to Change and Lack of Acceptance	Employees and stakeholders may resist the adoption of new AI technologies due to fear of job displacement, unfamiliarity with new systems, or a preference for traditional methods.	Bag et al., 2023; Gomera & Mafini, 2020; Gorbenko et al., 2022; Ismaeil & Lalla, 2024; Nyamekeh et al., 2025; Shankaran, 2024; Shrivastav, 2022; Singh & Maheswaran, 2023
	Lack of Specific Skills and Talent	A critical shortage of qualified professionals with the expertise to design, implement, and manage AI systems within SC has raised concerns.	Agrawal et al., 2019; Cannas et al., 2023; Husein et al., 2024; Nyamekeh et al., 2025; Raman & Selvaraj, 2024
	Silos and Lack of Collaboration	Disconnects between different departments or SC partners can impede the seamless integration and data sharing necessary for effective AI implementation.	Bag et al., 2023; Gorbenko et al., 2022; Khan et al., 2023; Orji & Ojadi, 2023; Shrivastav, 2022; Zain et al., 2024
	Lack of Top Management Support and Vision	Without strong leadership and a clear strategic vision from top management, AI initiatives may lack the necessary resources, prioritization, and organizational buy-in for successful implementation.	Chowdhury et al., 2022; Usmani et al., 2023
	Complex Change Management	The process of transitioning from traditional operations to AI-driven systems involves significant organizational restructuring, process re-engineering, and cultural shifts.	Ismaeil & Lalla, 2024; Nitsche et al., 2023; Shrivastav, 2022
Regulatory & Legal	Regulatory Compliance and Legal Frameworks	Navigating complex and evolving legal and regulatory landscapes related to AI, data governance, and liability can be challenging.	Addy et al., 2024; Ijiga et al., 2024; Ismaeil & Lalla, 2024; Kramer, 2024; Nisar et al., 2024; Rijanto, 2024; Shankaran, 2024
	Lack of Clear Policies and Guidelines	The absence of specific industry guidelines or government policies for AI implementation can create uncertainty and hinder adoption.	Agrawal et al., 2019; Rahman et al., 2020; Thomas & Sunny, 2025

(Source: Researcher's Findings)

Figure 1.
The Cross-impact Matrix of the Barriers to AI implementation in Desalination SC

	1 : High Imple	2 : Lack of Fu	3 : Poor Cash	4 : Data Quali	5 : Lack of St	6 : Insufficie	7 : Data Priva	8 : Algorithmi	9 : Scalabilit	10 : Resistance	11 : Lack of Sp	12 : Silos and	13 : Lack of To	14 : Complex Ch	15 : Regulatory	16 : Lack of Cl
1 : High Imple	0	1	0	0	0	1	0	1	0	0	0	1	1	0	0	0
2 : Lack of Fu	1	0	0	1	0	3	0	0	0	1	0	0	0	3	1	0
3 : Poor Cash	0	0	0	0	3	1	2	0	0	1	0	0	0	0	0	1
4 : Data Quali	0	0	2	0	0	0	0	2	0	0	0	0	0	1	0	0
5 : Lack of St	1	1	0	2	0	0	2	0	1	0	0	0	0	0	3	0
6 : Insufficie	0	0	2	0	0	0	0	1	0	2	1	1	1	0	0	0
7 : Data Priva	0	0	0	1	0	0	0	2	0	0	1	0	2	3	0	0
8 : Algorithmi	1	0	0	2	0	1	0	0	0	3	0	0	0	0	0	1
9 : Scalabilit	0	0	0	0	1	0	1	0	0	0	0	1	2	0	2	0
10 : Resistance	0	0	2	0	0	0	0	2	1	0	0	0	0	1	0	0
11 : Lack of Sp	1	0	0	2	0	2	0	0	2	0	0	0	0	1	0	1
12 : Silos and	0	0	0	0	0	0	0	0	0	3	0	0	1	0	2	0
13 : Lack of To	1	1	2	0	0	0	0	0	0	0	0	0	0	0	1	0
14 : Complex Ch	0	0	0	3	1	0	0	0	0	0	0	1	0	0	2	0
15 : Regulatory	0	0	1	0	0	0	1	0	0	1	0	1	0	0	0	1
16 : Lack of Cl	0	0	3	1	0	1	0	0	0	0	1	0	0	0	0	0

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(Source: Researcher's Findings)

After entering the questionnaire data into the software, the direct and indirect influences of the barriers to AI implementation in desalination SC were calculated, as presented in Tables 2 and 3.

Table 2.
The Direct Influence Matrix of the Identified Barriers AI Implementation in Desalination SC

N°	Variable	Total number of rows	Total number of columns
1	High Implementation and Running Costs	5	5
2	Lack of Funding and Capital	10	3
3	Poor Cash-Flow Management	8	12
4	Data Quality and Integration Issues	5	12
5	Lack of Standardization and Interoperability	10	5
6	Insufficient Technological Maturity	8	9
7	Data Privacy and Security Concerns	9	6
8	Algorithmic Transparency and Explainability	8	8
9	Scalability Issues	7	4
10	Resistance to Change and Lack of Acceptance	6	11
11	Lack of Specific Skills and Talent	9	3
12	Silos and Lack of Collaboration	6	5
13	Lack of Top Management Support and Vision	5	7
14	Complex Change Management	7	9
15	Regulatory Compliance and Legal Frameworks	5	11
16	Lack of Clear Policies and Guidelines	6	4
	Totals	114	114

(Source: Researcher's Findings)

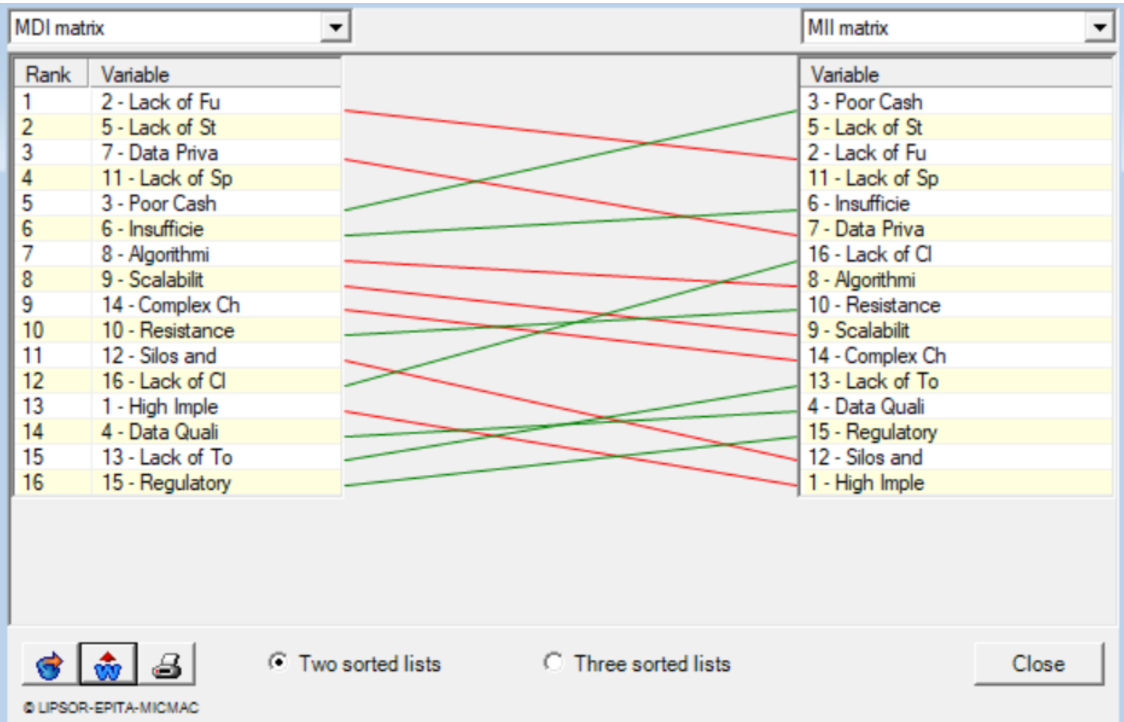
Table 3.
The Indirect Influence Matrix of the Identified Barriers to AI Implementation in Desalination SC

N°	Variable	Total number of rows	Total number of columns
1	High Implementation and Running Costs	238	196
2	Lack of Funding and Capital	448	114
3	Poor Cash-Flow Management	465	639
4	Data Quality and Integration Issues	271	539
5	Lack of Standardization and Interoperability	453	378
6	Insufficient Technological Maturity	402	322
7	Data Privacy and Security Concerns	386	383
8	Algorithmic Transparency and Explainability	355	478
9	Scalability Issues	301	170
10	Resistance to Change and Lack of Acceptance	316	597
11	Lack of Specific Skills and Talent	404	127
12	Silos and Lack of Collaboration	244	206
13	Lack of Top Management Support and Vision	274	250
14	Complex Change Management	285	372
15	Regulatory Compliance and Legal Frameworks	254	429
16	Lack of Clear Policies and Guidelines	357	253
	Totals	114	114

(Source: Researcher's Findings)

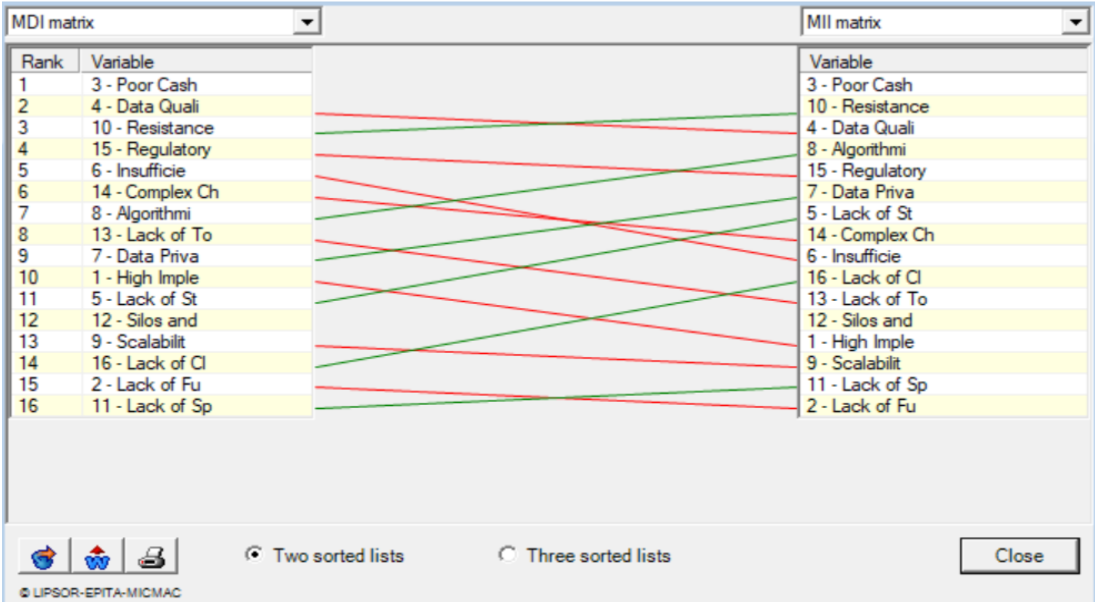
The factors were classified and ranked into two categories, driving and dependent, considering both their direct and indirect influences, until the variables reached the minimum possible difference in their rankings. The results of these calculations are presented in Figures (2) and (3).

Figure 2.
Ranking of Barriers Based on Their Influence in Direct and Indirect Impact Matrix



(Source: Researcher's Findings)

Figures 3.
Ranking of Barriers Based on Their Dependence in Direct and Indirect Impact Matrix



(Source: Researcher's Findings)

The barriers "Lack of Funding and Capital" and "Poor Cash Flow Management" ranked first in terms of influence and dependence, respectively. Table 4 presents the ranking of the barriers to AI implementation in desalination SC according to their influence and dependence, considering both direct and indirect effects.

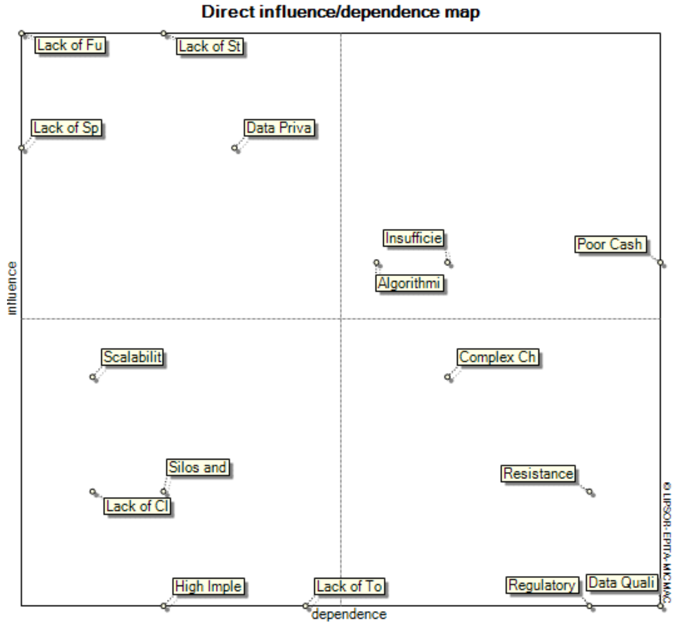
Table 4.
Direct and Indirect Scores of Influences and Dependence for the Barriers to AI Implementation

Rank	Label	Direct influence	Label	Direct dependence	Label	Indirect influence	Label	Indirect dependence
1	Lack of Fu	877	Poor Cash	1052	Poor Cash	852	Poor Cash	1171
2	Lack of St	877	Data Quali	1052	Lack of St	830	Resistance	1094
3	Data Priva	789	Resistance	964	Lack of Fu	821	Data Quali	988
4	Lack of Sp	789	Regulatory	964	Lack of Sp	740	Algorithmi	876
5	Poor Cash	701	Insufficie	789	Insufficie	737	Regulatory	786
6	Insufficie	701	Complex Ch	789	Data Priva	707	Data Priva	702
7	Algorithmi	701	Algorithmi	701	Lack of Cl	654	Lack of St	693
8	Scalabilit	614	Lack of To	614	Algorithmi	651	Complex Ch	682
9	Complex Ch	614	Data Priva	526	Resistance	579	Insufficie	590
10	Resistance	526	High Imple	438	Scalabilit	551	Lack of Cl	463
11	Silos and	526	Lack of St	438	Complex Ch	522	Lack of To	458
12	Lack of Cl	526	Silos and	438	Lack of To	502	Silos and	377
13	High Imple	438	Scalabilit	350	Data Quali	496	High Imple	359
14	Data Quali	438	Lack of Cl	350	Regulatory	465	Scalabilit	311
15	Lack of To	438	Lack of Fu	263	Silos and	447	Lack of Sp	232
16	Regulatory	438	Lack of Sp	263	High Imple	436	Lack of Fu	209

(Source: Researcher's Findings)

The most important output of the Mic Mac software is the influence–dependence map of the barriers. In this figure, the areas are divided into four sections, with the position of each variable indicating its type. Figure 4 presents the status of the factors accordingly.

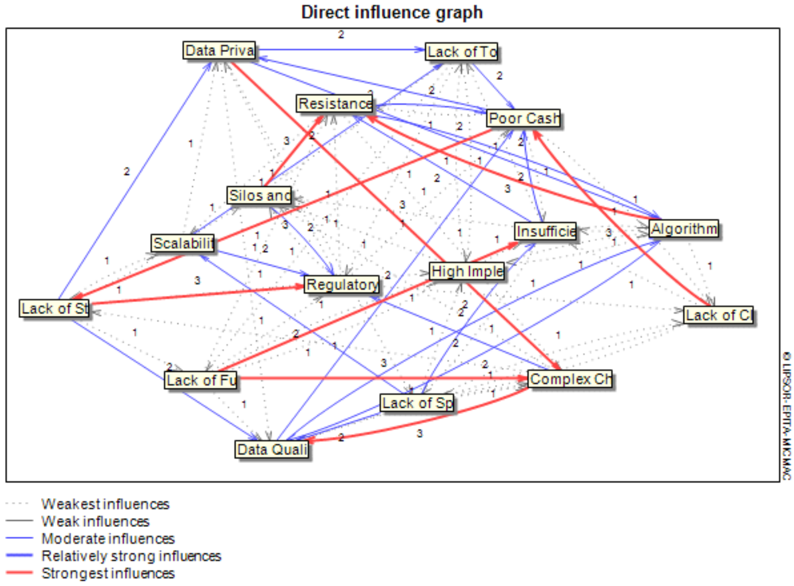
Figure 4.
Distribution of Influential and Dependent Barriers on the Coordinate Axes



(Source: Researcher's Findings)

As shown in Figure 4, the influence-dependence map indicates that the most influential variables are Lack of Funding and Capital, Lack of Standardization and Interoperability, Lack of Specific Skills and Talent, and Data Privacy and Security Concerns. In the next step, the Mic Mac software illustrated the relationships between the barriers' direct and indirect effects across five levels: very weak to very strong, weak to very strong, relatively strong to very strong, strong to very strong, and very strong. Some of these effects are depicted in Figures 5, 6, and 7.

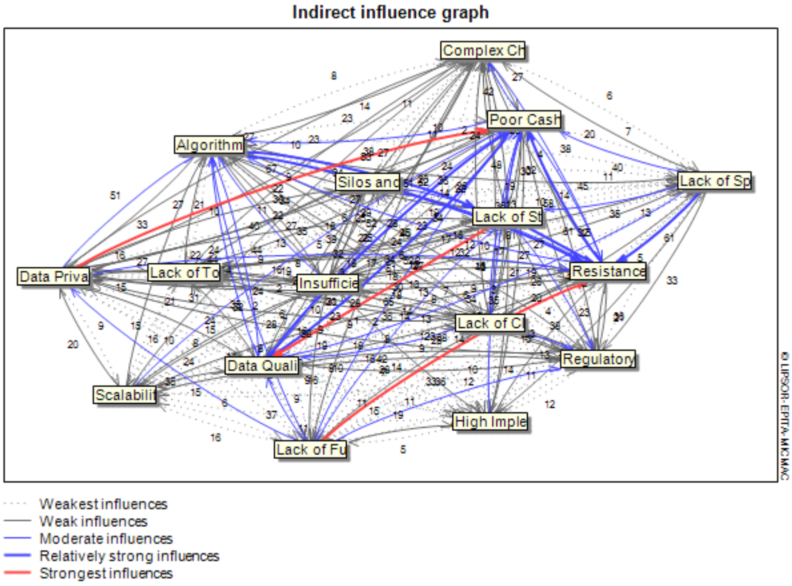
Figure 5.
The Diagram of the Direct Effects of Barriers (ranging from very weak to very strong)



(Source: Researcher's Findings)

Figure 6.

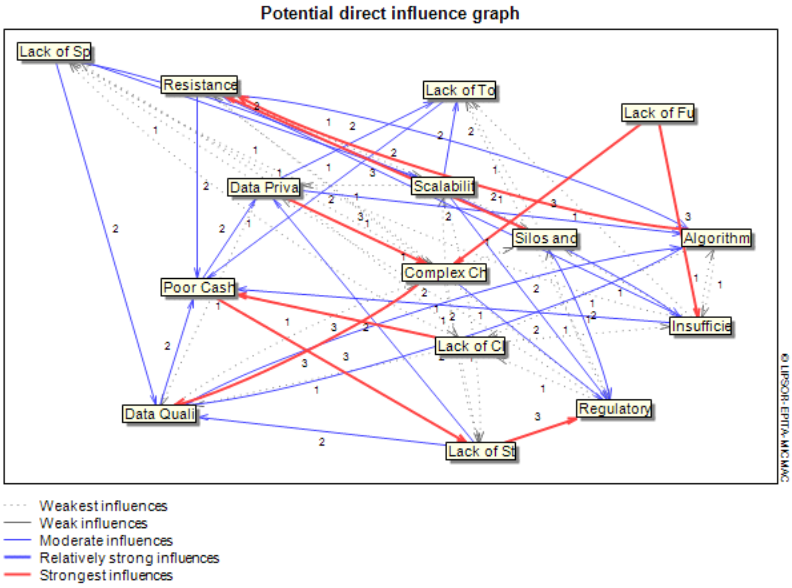
The Diagram of the Indirect Effects of Barriers (ranging from very weak to very strong)



(Source: Researcher's Findings)

Figure 7.

The Diagram of the Potential Direct Effects of Barriers on Each Other (ranging from very weak to very strong)



(Source: Researcher's Findings)

Discussion and Conclusion

The findings of this study indicated that although AI holds considerable potential for enhancing efficiency, sustainability, and decision-making in desalination SC, the realization of this potential is significantly constrained by structural and systemic barriers. The MICMAC analysis revealed that four fundamental barriers exert the greatest influence on other factors and serve as critical bottlenecks in the successful implementation of AI. First, the lack of funding and capital is among the most significant obstacles, as it directly restricts the provision of infrastructure, workforce training, and investment in emerging technologies, thereby hindering the large-scale deployment of AI projects. This factor is not only an independent barrier but also a driver of many other challenges, suggesting that without stable financial support, overcoming the remaining obstacles becomes increasingly difficult. Second, the absence of standardization and interoperability among systems and technologies complicates the integration of AI into desalination SC. The lack of a common data language and unified frameworks lead to fragmented operations and reduces synergy across different segments of the chain. Third, the lack of specific skills and talent in the domains of AI and SC management poses a serious threat to the development and maintenance of intelligent systems. The lack of such technical skills, even in the presence of adequate financial and infrastructural resources, can expose projects to a high risk of failure. Fourth, given the sensitive nature of operational and environmental data in the water sector, data privacy and security concerns represent a fundamental challenge for organizational adoption and regulatory trust. This finding aligns with evidence from career success research in higher education, where systemic constraints—such as centralized governance, resource inequalities, and institutional inertia—limit professional advancement (Khanjani et al., 2023). Just as structural barriers constrain individual career trajectories, they similarly restrict the large-scale adoption of transformative technologies such as AI.

Taken together, the results highlighted that achieving successful AI implementation in desalination SC requires an integrated, multi-level approach. Solutions must simultaneously focus on strengthening financial capacity through investment incentives, developing and enforcing common standards, designing educational programs to cultivate specialized skills, and establishing robust frameworks for data protection. Furthermore, collaboration among governments, private industry, and research institutions will be essential in overcoming barriers and accelerating AI adoption. Ultimately, by identifying the key barriers and mapping their interrelationships, this study has provided a clear roadmap for future action and can serve as a foundation for strategic decision-making and policy development in the pursuit of sustainable water resource management.

From a practical perspective, policymakers and industry leaders should prioritize the development of financial support mechanisms such as low-interest loans and investment incentives to foster the development of digital infrastructure. Also, implementation of knowledge management could help in the process (Sadeghi et al., 2013). Establishing national and regional centers for standardization and data exchange could further strengthen integration and collaboration across SC actors. Expanding interdisciplinary educational programs and fostering university–industry partnerships for training skilled professionals represent a critical pathway to closing the talent gap. Finally, the adoption of advanced cybersecurity technologies and the formulation of clear data protection regulations will play a vital role in building trust and facilitating the acceptance of AI solutions.

Nevertheless, this study is not without limitations. First and foremost, the analysis was primarily based on expert opinions and secondary data, which may not fully capture operational perspectives across diverse contexts. Second, the dynamic and rapidly evolving nature of AI technologies and regulatory frameworks may necessitate future revisions of some findings. Third, the focus of this research was limited to desalination SC, and generalizing the results to other water or energy sectors will require additional investigation. Therefore, future studies are encouraged to employ broader field data, apply more advanced quantitative methods, and conduct cross-industry comparisons in order to develop more precise and practical pathways for overcoming barriers and enhancing the role of AI in the management of critical resources.

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