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Examining the Challenges of Implementing Artificial Intelligence in the Water Supply Sector: A Case Study

Moza S. M. A. Almheiri [1], Hamdi Bashir [1,2,*], Udechukwu Ojiako [3,4,5], Salah Haridy [1,2,6] and Mohammed Shamsuzzaman [1,2]

1 Department of Industrial Engineering and Engineering Management, College of Engineering, University of Sharjah, Sharjah 27272, United Arab Emirates; u20201424@sharjah.ac.ae (M.S.M.A.A.); sharidy@sharjah.ac.ae (S.H.); mshamsuzzaman@sharjah.ac.ae (M.S.)
2 Sustainable Engineering Asset Management Research Group, University of Sharjah, Sharjah 27272, United Arab Emirates
3 Design, Manufacturing & Engineering Management, University of Strathclyde, Glasgow G1 1XQ, UK; udi.ojiako@strath.ac.uk
4 Centre for Systems Studies, University of Hull, Hull HU6 7TS, UK
5 Johannesburg Business School, University of Johannesburg, Johannesburg 2092, South Africa
6 Benha Faculty of Engineering, Benha University, Benha 13518, Egypt
* Correspondence: hbashir@sharjah.ac.ae

Abstract: Challenges in the water supply sector have hindered the advanced implementation of artificial intelligence (AI) compared to other sectors. These challenges have not been sufficiently examined in the existing literature. An empirical study was conducted within a public utilities organization in the United Arab Emirates (UAE) to address this gap. An integrated approach combining interpretive structural modeling (ISM) and fuzzy cross-impact matrix multiplication applied to classification (MICMAC) analysis was utilized to identify the critical challenges and to model and analyze the relationships among them. The ISM model provides significant advantages by enabling decision-makers to visualize complex interactions, supporting the development of an effective AI implementation strategy. The strategy should prioritize four critical challenges: the lack of technical skills and knowledge, the limited availability of ready-to-use AI solutions, inadequate water infrastructure, and concerns regarding privacy and data security. These challenges were identified based on their positioning at the lowest level of the ISM model and their classification as independent in the fuzzy MICMAC analysis. Addressing these four challenges will help to mitigate the remaining six. The study's findings and implications are expected to offer valuable guidance for decision-makers in implementing AI technologies within water supply organizations, both in the UAE and in countries with similar environments.

Keywords: water supply sector; artificial intelligence; implementation; challenges; UAE

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1. Introduction

Water is essential for people, plants, animals, and for the economic progress of any country. However, one in four people globally lack access to clean water and face challenges with water purity. Moreover, according to some estimates, two-thirds of the world's population is situated in regions with water scarcity for several reasons, including increasing consumption, population growth, and the ramifications of climate change [1,2]. The challenge is intensifying, with an expected increase in the urban population from 3.9 billion in 2014 to 6.3 billion by 2050 [3]. While the rate of urbanization will differ by country, it is especially prominent in Asia and Africa, with almost 90% of the growth in urban areas. As a result, these metropolitan regions will depend heavily on existing water supplies, presenting mounting challenges for water management. If this trend continues, by 2030, the water demand could surpass availability by 40% [4].

Certain regions, including the Middle East and North Africa, are recognized as some of the most water-scarce regions globally [5]. These regions account for only about 1.4 percent of the world's renewable freshwater resources. Physical water scarcity is a frequent issue in arid and semi-arid climates. For instance, nations such as the United Arab Emirates (UAE) and Saudi Arabia struggle to meet their water needs due to inherently low rainfall levels and limited water resources [5,6]. In contrast, some countries face severe environmental challenges stemming from overconsumption of water, which accelerates environmental degradation. The Aral Sea basin, shared by Kazakhstan and Uzbekistan, illustrates this issue, where extensive irrigation practices have drastically reduced water resources. This overuse has resulted in significant ecological damage, compromising clean water availability for both human needs and ecological balance [7].

At this critical stage, organizations in the water supply sector need to revolutionize their water management systems into more sustainable, intelligent, and resilient frameworks by adopting Water 4.0 technologies. According to Sedlak [8], the initial phases of water technology evolution were as follows: Water 1.0 was centered on the development of centralized drinking water systems, Water 2.0 focused on the development of sewer infrastructures for wastewater management, while Water 3.0 featured wastewater treatment to mitigate pollution and environmental harm.

By employing a range of emerging technologies such as artificial intelligence, big-data analytics, cloud computing, cyber-physical systems, and the Internet of Things, Water 4.0 can provide a better understanding of complex water management issues, enabling it to be used in early warning, production, and decision-making processes. Additionally, Water 4.0 facilitates optimal water supply system management, allowing users to utilize limited water resources more efficiently [9]. However, despite the considerable potential benefits of these technologies, their application in the water sector is relatively less extensive than their utilization in other sectors, including energy, healthcare, manufacturing, or transportation [10,11].

Among these technologies, artificial intelligence (AI), in particular, has seen limited adoption in water. Most of the reported work (a sample of which is discussed in Section 2.3) has been conducted by researchers or AI vendors rather than practitioners, making it challenging to assess how these advancements are perceived by water utilities [12]. To explore the extent to which water utilities have actually implemented AI technologies, a survey by Rapp et al. [12] revealed that only 24% of a random sample of 49 major water utilities in the United States had adopted some form of AI technology. These applications were largely experimental, manual, or partial models, falling short of fully integrated, continuously operating systems. In the UAE, a leading utility organization—the subject of this case study—has yet to implement any AI-related initiatives.

The factors contributing to this limited adoption of AI in the water sector remain underexplored in the existing literature. To address this gap, this research investigated the challenges associated with implementing AI technologies in the aforementioned utility organization. As one of the few studies to address this issue in the water supply sector, it is expected to provide insights into sector-specific challenges and offer a structured approach to addressing them, which could be valuable for other utilities and related sectors.

The following is the structure of the rest of this article. The following section briefly reviews the pertinent literature concerning artificial intelligence, both in the context of the UAE and its implementation in the water supply sector. Subsequently, we outline the methodological approach employed in our study. Following that, we present the obtained findings and engage in a comprehensive discussion of the results. Then, we proceed with a discussion on addressing the most critical challenges identified. Last are the final remarks, limitations, and recommendations for the future, which are presented in the conclusions section.

2. Literature Review

2.1. Artificial Intelligence

Artificial intelligence (AI) is a quickly developing field that has revolutionized numerous parts of daily living. It has its roots in the mid-twentieth century when computer scientists first began to explore the possibility of machines that could think and learn like humans [13]. In 1950, Alan Turing first identified the idea of AI in the "Turing Test", originally known as the imitation game [14]. Since then, technology has rapidly grown and matured. Today, we are in an age where machines excel in tasks that necessitate intelligent interactions, thanks to their ability to connect and visualize data. As we transition to the era of Industry 4.0, the progress of AI is directed towards integrating it with other technologies like big data and cloud computing. This integration enables AI to tackle massive tasks and expand its applications across various fields. Thus, AI is not a new field of study, but it has garnered renewed attention recently because of its remarkable advancements [15] and intensified policy focus [16].

UNESDOC [17] defined AI systems as "technological systems capable of processing information in a manner that imitates intelligent behavior". Such systems typically encompass control, learning, perception, planning, prediction, or reasoning functionalities. AI systems consist of various approaches and technologies, which may include, among others, artificial neural networks [18]; case-based reasoning [19]; cognitive mapping [20]; cyber-physical systems [21,22], including autonomous machines and vehicles, computer vision, facial and image recognition, human–computer interfaces, robotics, and speech recognition; fuzzy logic [23,24]; supervised and unsupervised machine learning [25]; machine reasoning [26], such as knowledge representation and reasoning, optimization, planning, predictive analytics, search, scheduling; multi-agent systems [27]; and natural language processing [28].

2.2. Artificial Intelligence in the UAE

Many countries worldwide are trying to integrate into the AI-powered digital economy, which is forecasted to contribute approximately USD 15.7 trillion to the global economy by 2030 [29]. In Africa and the Middle East, the AI market is anticipated to expand from USD 500 million in 2020 to USD 8.4 billion by 2026, representing a compound annual growth rate of 47.8%. In 2020, the UAE's AI market was valued at USD 290 million [30]. It is projected to grow at a compound annual growth rate of 28.54% from 2024 to 2030, with the market size expected to reach USD 4.29 billion by 2030 [31]. Such rapid growth highlights the country's commitment to advancing AI and boosting economic development. This growth aligns with the UAE government's Strategy for Artificial Intelligence (AI), launched in 2017 to improve performance across all sectors by implementing a smart digital system capable of efficiently addressing challenges. The goal is to establish the UAE as a global AI investment and innovation leader while developing a high-value market [32]. The AI strategy also complements the UAE Centennial 2071 plan, which focuses on preparing future generations with the necessary skills and knowledge to navigate global changes, positioning the country to become the world's top nation by 2071.

To realize the UAE's strategy objectives for AI, a Minister of State for Artificial Intelligence was established to facilitate the adoption of more recent AI technologies across governmental sectors [32]. An AI Council has also been formed, comprising ten members from governmental entities, to explore the necessary foundational infrastructure to support AI. AI Council members and the Minister of State for AI are to collaborate closely in developing government regulations to ensure the safe and responsible use of AI technologies across the nation's diverse sectors, including the water supply sector. Examples of these regulations include the AI Ethics Principles and Guidelines, which emphasize transparency, accountability, fairness, and the protection of human rights in AI applications [33].

2.3. AI Implementation in the Water Supply Sector

The role of the water supply sector in any country is crucial in ensuring access to clean and safe water for its communities. However, this sector encounters various general challenges. First, it operates primarily in the public domain [34], with water considered something that should be accessible to all with adequate quality and quantity [35]. Second, water management involves several conflicting constraints, including scarcity, limited space, and the availability of funds for constructing and upgrading essential infrastructure [36]. Third, many water-associated problems have a spatial dimension [37], often accompanied by specialized infrastructure requirements [38]. Lastly, particularly concerning climate change, uncertainty adds to the numerous challenges in the water sector [39].

The challenges mentioned above, along with others, can be effectively addressed through the adoption of AI technologies. Table 1 presents a sample of these applications, illustrating how AI can be applied across various domains, including operations management, modeling, optimization, prediction, and forecasting. These applications demonstrate the significant potential of AI to enhance efficiency, resilience, and sustainability in the water sector, empowering water utilities and resource managers to tackle pressing challenges more effectively.

Table 1. Sample of applications.

Application Area	Sample of Applications	Reference(s)
Operations management	Detection of accidental water contamination	[40]
	Detection of damage to pipes in an earthquake's aftermath	[41]
Modeling	Identifying and managing leaks	[42–44]
	Modeling water quality	[45,46]
	Extracting surface water	[47]
	Inferring body of water types from urban high-resolution remote sensing images	[48]
Optimization	Developing and applying a conceptual model for aquifer vulnerability assessment	[49]
Prediction and forecasting	Determining an optimal policy for releasing water from a reservoir	[50]
	Optimizing reservoir operating rules	[51]
	Identifying water pollution characteristics and trace sources	[52]
	Prediction of water demand	[53–56]
	Prediction of groundwater level	[57,58]
	Forecasting the formation of trihalomethanes	[59]

In operations management, AI enables real-time detection and response to critical issues. For example, systems that detect accidental water contamination [40] or assess damage to pipes after earthquakes [41] empower utilities to mitigate risks promptly, ensuring public safety and maintaining operational continuity. Modeling applications further extend the capabilities of water management by identifying and managing leaks [42–44], modeling water quality [45,46], and extracting surface water [47]. Advanced techniques, such as using high-resolution remote sensing for inferring body of water types [48] or conducting aquifer vulnerability assessments [49], provide decision-makers with valuable insights to manage water resources more effectively.

Optimization is another key area where AI offers significant value. For instance, it facilitates the determination of optimal water release policies [50] and reservoir operation rules [51], allowing for more efficient resource allocation and reduced water wastage. Predictive and forecasting applications are vital for proactive water management. These include predicting water demand [53–56], forecasting groundwater levels [57,58], and anticipating the formation of harmful substances such as trihalomethanes [59]. These predictive tools enable utilities to prepare for future challenges, ensuring the sustainability and quality of water supply. However, despite these benefits, the water supply sector, like other industries, faces unique challenges that may hinder the adoption of AI technologies.

While numerous studies have examined the challenges of implementing AI in sectors like construction [60], manufacturing [61,62], public services [63,64], and healthcare [65–69], research focusing on the unique challenges in the water supply sector remains limited. In this context, Fu et al. [70] explored the transformative potential of AI in modernizing urban water infrastructure (UWI) to enhance reliability, resilience, and sustainability. The study aimed to provide a comprehensive framework aligning AI with UWI development through five key pathways: decentralization, circular economy, greening, decarbonization, and automation. Through a literature review and conceptual analysis, the authors synthesized insights to offer a comprehensive perspective. The study highlights the vital role of AI analytics—descriptive, diagnostic, predictive, and prescriptive—in enhancing UWI performance while addressing challenges related to cyber-physical infrastructure, institutional governance, socio-economic systems, and technological development. Key challenges include limited data availability, insufficient monitoring systems, high implementation costs, and public resistance. However, the study's reliance on secondary data and its predominant focus on cyber-physical aspects, with less emphasis on social and behavioral dynamics, limits its ability to provide actionable insights or address the complexities of AI integration comprehensively. Rather than relying solely on a conceptual analysis, Vekaria [71] employed surveys and pilot interviews to evaluate AI implementation across water utilities, emphasizing diversity in scale and geography. Responses were gathered from 10 utilities—6 large-scale, 2 medium-scale, and 2 small-scale—spanning various states in the United States, with all participants being public utilities. The surveys, structured around the seven pillars of the aiWATERS framework, aimed to capture AI practices, challenges, and adoption willingness. Supported by a literature review, the study identified challenges include trust and transparency, data management-related challenges, ethical and social concerns, and domain knowledge integration challenges. Despite uncovering valuable insights, the study acknowledged limitations in its sample size and emphasized the need for a broader validation of the aiWATERS framework.

3. Methodology

This research employed a case study approach to identify the critical challenges (CC_s) to artificial intelligence implementation in the water sector, model the associations among these CC_s, and categorize them based on their dependence power and driving power. The subject of the case study was a prominent utility provider in the UAE known for generating, transmitting, and distributing electricity, water, and gas. This organization was selected because it had yet to implement any AI-related initiatives in the water sector. However, it is currently moving towards adopting AI to align with the strategic goals for AI set by the UAE. The methodological approach involved combining interpretive structural modeling (ISM) with fuzzy cross-impact matrix multiplication applied to classification (MICMAC) analysis to achieve these objectives.

ISM is a well-known process that helps to identify the connections among components that describe a problem or issue [72]. It allows for the modeling of the variables and the structure of their interrelationships. Participants can share insights and develop a mutual grasp of how the variables interrelate without needing to understand the complex underlying mathematics. Their input is converted into a visual model consisting of nodes and arcs. The nodes symbolize the variables involved, and the arcs depict the directionality of the relationships. ISM is often combined with MICMAC analysis, which was introduced by Duperrin and Godet [73].

The purpose of MICMAC analysis is to classify variables into four groups based on their driving and dependence powers. The first group consists of autonomous variables, characterized by having both low driving and low dependence power. The second group includes dependent variables, which display high dependence power but low driving power. The third group comprises linkage variables demonstrating strong driving and dependence powers. Lastly, the fourth group contains independent variables, marked by high driving power but low dependence power.

Researchers generally employ two versions of MICMAC analysis: the classical version (e.g., [74–76]) and the fuzzy version (e.g., [77–79]). The classical version considers only binary relationships, while the fuzzy version incorporates the strength of relationships using fuzzy set theory. Due to this advantage, we adopted the fuzzy version for our analysis.

Comparatively, when assessing the merits of ISM and fuzzy MICMAC against other modeling techniques such as the Decision-Making Trial and Evaluation Laboratory (DEMATEL), developed by the Geneva Research Centre of the Battelle Memorial Institute [80,81], and the Analytic Network Process developed by Saaty [82], several distinctions become apparent. DEMATEL is proficient in mapping out cause-and-effect relationships among system factors but falls short in outlining a clear hierarchical organization of these relationships. On the other hand, ISM, enhanced by fuzzy MICMAC analysis, excels in identifying and visualizing a structured stratification of variables, categorizing them based on their influence and dependency within the system. This ability to demarcate a clear hierarchy among variables provides a strategic advantage in pinpointing critical intervention leverage points. Additionally, while ANP offers a sophisticated framework for addressing feedback and interdependencies within a network of criteria and alternatives, its complexity often limits practical application.

As depicted in Figure 1, the process of utilizing ISM–fuzzy MICMAC analysis for modeling and analyzing *CCs* consists of three main stages:

1. Identifying the *CCs* to implement artificial intelligence in the water sector;
2. Examining the contextual relationships between the *CCs*;
3. Categorizing the *CCs* according to their driving and dependence power.

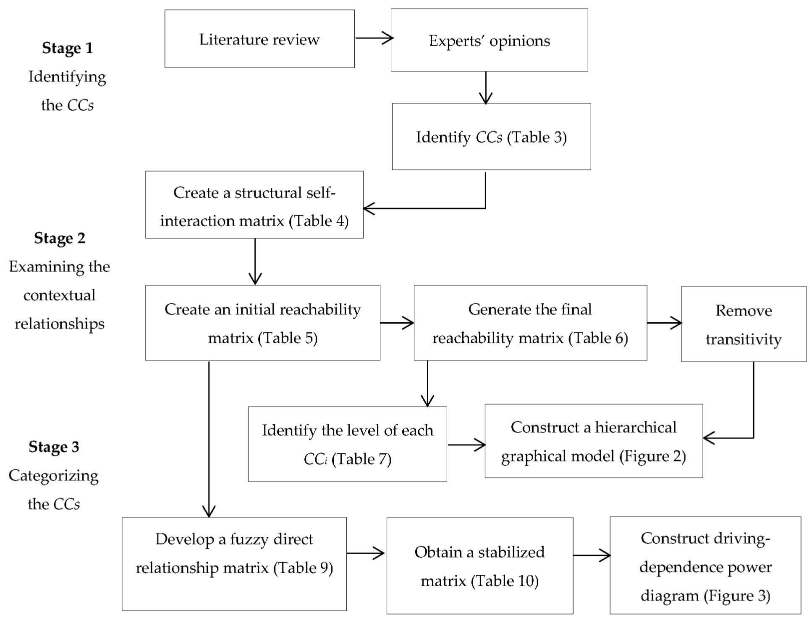

Figure 1. Flow chart for ISM–fuzzy MICMAC analysis.

3.1. Identifying CC_S

For identifying *CCs*, a preliminary list of 29 challenges was compiled by reviewing recent studies exploring AI integration across various sectors [60–71]. Subsequently, a panel of six experts, in addition to one of the co-authors, was formed. These experts, who have diverse backgrounds, positions, and experience levels (as shown in Table 2), play a crucial role in implementing any new processes or technologies in the case study.

Table 2. Demographic information of experts.

Job Title	Years of Experience	Department
Deputy Manager	6	Research and Development
Head	6	Water Planning Section
Head	15	Water Services Section
Operations Engineer	3	Water Planning Section
Operations Engineer	6	Project Management Office

During a brainstorming meeting where the preliminary list of 29 challenges was used as a reference (which experts could alter, expand, or reduce), the experts pinpointed ten challenges as the *CCs* for implementing AI in their organization. Brainstorming is a widely used group approach for generating ideas, enabling the extraction of profound knowledge in a relatively brief timeframe [83]. Table 3 presents a summary of each of the identified *CCs*.

Table 3. Identified *CCs*.

S/N	CC_i	Description
1	High implementation cost	AI systems require specialized hardware, such as GPUs, and compatible software, which can be costly to purchase and maintain. Besides the hardware and software aspects, implementing AI systems requires the recruitment of proficient specialists possessing specialized skills and expertise, typically commanding high salaries.
2	Privacy and data security concerns	The reliance of AI systems on substantial volumes of sensitive data poses a challenge in preserving the confidentiality of this information, especially considering the growing frequency of data breaches and cyber-attacks.
3	High R&D cost	Developing new AI technologies and improving existing ones requires significant investment in R&D, which can be expensive for organizations.
4	Trust and transparency-related issues	AI systems are occasionally perceived as enigmatic entities, implying that their internal mechanisms and decision-making processes are not easily comprehensible, even to the users or developers involved.
5	The bias problem	The effectiveness of AI systems is directly tied to the quality of their training data. If the training data for an AI system are biased, the resulting output will also be biased.
6	Lack of data managementsystem	A lack of a comprehensive data management system can hinder the availability, quality, accessibility, privacy, security, and compliance aspects of data.
7	Lack of technical skills and knowledge	Implementing AI systems requires specialized technical skills and knowledge in developing and integrating AI systems into existing infrastructure and deploying them in real-world settings.
8	Responsibility and accountability-related issues	AI systems are designed to make decisions and take actions without human intervention, making it challenging to determine who is responsible for their outcomes. This can lead to questions about accountability in the event of unintended consequences or harm caused by AI systems.
9	Limited ready-to-use AI solutions	There is a scarcity of readily available AI solutions that can be implemented in the water industry.
10	Incompetent water infrastructure	Incompetent water infrastructure includes outdated systems, limited connectivity, insufficient computing infrastructure, and the necessity for infrastructure upgrades to facilitate the integration of AI.

3.2. Examining the Contextual Relationships Between the CCs

In this stage, the relationships between the identified *CCs* were examined through the following five sequential steps:

- Creating a structural self-interaction matrix (SSIM);
- Creating an initial reachability matrix from the SSIM;
- Generating the final reachability matrix;
- Identifying the level of each CC_i;
- Constructing an ISM hierarchical graphical model.

During a separate brainstorming session, the experts' panel created the SSIM (Table 4) through a pairwise comparison of *CCs* using the following symbols:

1. V indicates that CCi influences CCj (a forward relationship).
2. A indicates that CCj influences CCi (a backward relationship).
3. X signifies bidirectional relationships, indicating that CCi and CCj influence each other.
4. O indicates that CCi and CCj are unrelated.

Table 4. Structural self-interaction matrix.

S/N	10	9	8	7	6	5	4	3	2	1
1	*A*	*A*	*O*	*A*	*A*	*O*	*O*	*A*	*O*	
2	*A*	*O*	*V*	*O*	*O*	*O*	*V*	*V*		
3	*A*	*A*	*O*	*A*	*A*	*O*	*O*			
4	*O*	*O*	*X*	*A*	*A*	*O*				
5	*O*	*O*	*O*	*A*	*A*					
6	*A*	*O*	*O*	*O*						
7	*O*	*O*	*O*							
8	*O*	*O*								
9	*O*									
10										

As illustrated in Table 5, the SSIM was transformed into an $m \times m$ initial reachability matrix, where m is the total number of *CCs.* This transformation involved replacing the four symbols (V, A, X, or O) with ones and zeros, according to the following substitution rules:

- "If the (i, j) entry in the SSIM is V, then the (i, j) entry in the initial reachability matrix becomes one, and the (j, i) entry becomes zero.
- If the (i, j) entry in the SSIM is A, then the (i, j) entry in the initial reachability matrix becomes zero, and the (j, i) entry becomes one.
- If the (i, j) entry in the SSIM is X, then the (i, j) entry in the initial reachability matrix becomes one, and the (j, i) entry becomes one.
- If the (i, j) entry in the SSIM is O, then both the (i, j) and (j, i) entries in the initial reachability matrix become zeros" [84].

Table 5. Initial reachability matrix.

S/N	1	2	3	4	5	6	7	8	9	10
1	1	0	0	0	0	0	0	0	0	0
2	0	1	1	1	0	0	0	1	0	0
3	1	0	1	0	0	0	0	0	0	0
4	0	0	0	1	0	0	0	1	0	0
5	0	0	0	0	1	0	0	0	0	0
6	1	0	1	1	1	1	0	0	0	0
7	1	0	1	0	1	0	1	0	0	0
8	0	0	0	1	0	0	0	1	0	0
9	1	0	1	0	0	0	0	0	1	0
10	1	1	1	0	0	1	0	0	0	1

The initial reachability matrix, however, only captures the direct relationships between *CCs*. The principle of transitivity was utilized to obtain a final reachability matrix that counts for direct and indirect relationships, as shown in Table 6. This matrix was obtained by repeatedly multiplying the initial reachability matrix by itself using Boolean matrix multiplication until it reached a stable state.

Table 6. Final reachability matrix.

S/N	1	2	3	4	5	6	7	8	9	10
1	1	0	0	0	0	0	0	0	0	0
2	1	1	1	1	0	0	0	1	0	0
3	1	0	1	0	0	0	0	0	0	0
4	0	0	0	1	0	0	0	1	0	0
5	0	0	0	0	1	0	0	0	0	0
6	1	0	1	1	1	1	0	1	0	0
7	1	0	1	0	1	0	1	0	0	0
8	0	0	0	1	0	0	0	1	0	0
9	1	0	1	0	0	0	0	0	1	0
10	1	1	1	1	1	1	0	1	0	1

After constructing the final reachability matrix, the next step was determining the hierarchical level of each CC_i within the ISM graphical model. This was achieved by identifying the overlap between the antecedent and reachability sets for each CC_i. The reachability set of a given CC_i includes all the *CCs* it can influence, while the antecedent set consists of the *CCs* that can influence it. Once the reachability and antecedent sets for each CC_i were established, their intersection was determined. Any CC_i where the antecedent set and intersection set were identical was classified as a bottom-level CC_i in the ISM hierarchical model. After identifying the bottom-level *CCs*, they were removed from the reachability and antecedent sets. This process was repeated to identify the next hierarchical level of *CCs*. The iterative process continued until all the *CCs* were organized into four levels, as displayed in Table 7.

Table 7. Levels of the *CCs*.

S/N	Reachability Set	Antecedent Set	Level
1	1	1, 2, 3, 6, 7, 9, 10	IV
2	1, 2, 3, 4, 8	2, 10	II
3	1, 3	2, 3, 6, 7, 9, 10	III
4	4, 8	2, 4, 6, 8, 10	III
5	5	5, 6, 7, 10	III
6	1, 3, 4, 5, 6, 8	6, 10	II
7	1, 3, 5, 7	7	I
8	4, 8	2, 4, 6, 8, 10	III
9	1, 3, 9	9	I
10	1, 2, 3, 4, 5, 6, 8, 10	10	I

The last step of this stage involved constructing a graphical model that visualizes the relationships between the identified *CCs*. Transitivity was removed to simplify the model and make it easier to interpret, resulting in a simple hierarchy graphical model with nodes and arcs. The nodes represent the *CCs* and are positioned in the model according to their identified levels. The arcs indicate the presence of direct interactions between them. Specifically, if CC_i directly affects CC_j, a directed arc is drawn from CC_i to CC_j. The constructed hierarchy graphical model is shown in Figure 2. As shown in this figure, this model organizes the *CCs* into different levels. At the bottom level, a lack of technical skills and knowledge (*CC* 7), limited ready-to-use AI solutions (*CC* 9), and incompetent water infrastructure (*CC* 10) are positioned, highlighting them as fundamental issues that impact higher-level *CCs*. At the top of the hierarchy, high implementation cost (*CC* 1) is shown as an ultimate challenge, influenced by the *CCs* below.

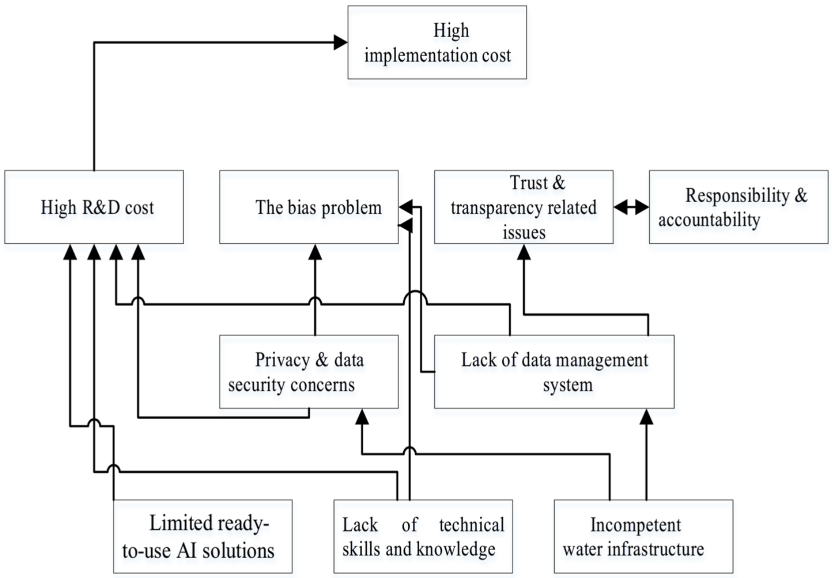

Figure 2. ISM-based model.

3.3. Categorizing the CCs

To categorize *CCs*, we started by substituting the "1" values in the initial reachability matrix with weighted values that reflect the strength of each relationship. This was carried out following the principles of fuzzy set theory [85]. Various forms of membership functions are used in this context, but the triangular function is the most widely adopted [86]. Equation (1) describes the method for determining the lower bound ("p"), the upper bound ("r"), and the value ("q") for the triangular membership function "$\mu_{\tilde{A}}(x)$" in a fuzzy set "A", where $p < q < r$.

$$\mu_{\tilde{A}}(x) = \left[\begin{array}{cc} 0 & x < p \\ \frac{x-p}{q-p} & p \leq x \leq q \\ \frac{r-x}{r-q} & q \leq x \leq r \\ 0 & x > r \end{array} \right] \quad (1)$$

The weights were assigned via the following process. During a subsequent brainstorming session, the panel of experts assessed the strength of the relationships between the *CCs* using the linguistic variables outlined in Table 8. These variables were then converted into their corresponding triangular fuzzy numbers. Once these fuzzy numbers were transformed into the best nonfuzzy performance (BNP_{ij}) values, as defined by Equation (2), the matrix of fuzzy direct relationships was created, as shown in Table 9.

$$BNP_{ij} = \frac{[(r-p)+(q-p)]}{3} + p \quad (2)$$

Table 8. The scale of fuzzy linguistic variables.

Linguistic Variable	Triangular Fuzzy Number
Very low influence	(0.0, 0.1, 0.3)
Low influence	(0.1, 0.3, 0.5)
Medium influence	(0.3, 0.5, 0.7)
High influence	(0.5, 0.7, 0.9)
Very high influence	(0.7, 0.9, 1.0)
Complete influence	(1.0, 1.0, 1.0)

Table 9. The fuzzy direct relationship matrix.

S/N	1	2	3	4	5	6	7	8	9	10
1	0	0	0	0	0	0	0	0	0	0
2	0	0	0.5	0.9	0	0	0	0.9	0	0
3	0.3	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0.7	0	0
5	0	0	0	0	0	0	0	0	0	0
6	0.3	0	0.3	0.5	0.5	0	0	0	0	0
7	0.9	0	0.9	0	0.5	0	0	0	0	0
8	0	0	0	0.5	0	0	0	0	0	0
9	0.7	0	0.9	0	0	0	0	0	0	0
10	0.7	0.5	0.7	0	0	0.9	0	0	0	0

Apart from direct relationships, there are also indirect relationships among *CCs*. To consider both types of relationships, we repeatedly performed fuzzy matrix multiplication on the fuzzy direct relationship matrix until a stable matrix was obtained (Table 10). By totaling all the values in column j of this matrix, the dependence power of CC_j was determined. In contrast, the driving power of CC_i was calculated by summing all the values in row i of the same matrix. Based on these calculated values, a driving-dependence power diagram was constructed, divided into four quadrants: autonomous, dependent, independent, and linkage. This diagram is depicted in Figure 3.

Table 10. Stabilized matrix.

S/N	1	2	3	4	5	6	7	8	9	10
1	0	0	0	0	0	0	0	0	0	0
2	0.3	0	0.5	0.9	0	0	0	0.9	0	0
3	0.3	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0.7	0	0
5	0	0	0	0	0	0	0	0	0	0
6	0.3	0	0.3	0.5	0.5	0	0	0.5	0	0
7	0.9	0	0.9	0	0.5	0	0	0	0	0
8	0	0	0	0.5	0	0	0	0	0	0
9	0.7	0	0.9	0	0	0	0	0	0	0
10	0.7	0.5	0.7	0.5	0.5	0.9	0	0.5	0	0

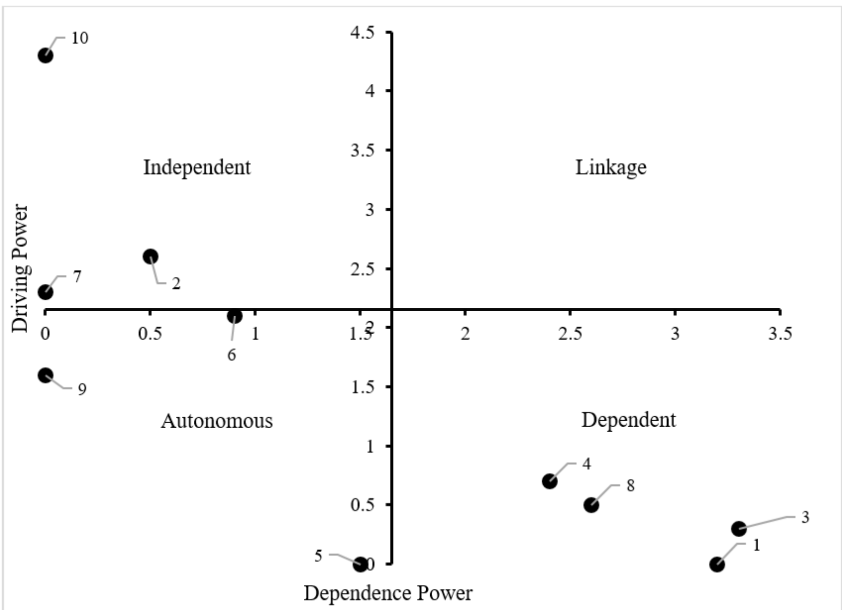

Figure 3. Driving-dependence power diagram.

4. Findings and Discussion

A UAE public utility organization was chosen as a case study to examine the challenges of implementing AI in the water supply sector, employing an integrated approach involving ISM–fuzzy MICMAC analysis. The researchers identified ten *CCs* by reviewing the literature and consulting with experts. Two observations can be made regarding these *CCs*. Firstly, several of them—specifically, incompetent infrastructure, high implementation costs, lack of technical skills and knowledge, and limited ready-to-use AI solutions—align to some extent with challenges identified in the broader literature [87]. For example, Luthra et al. [62] highlighted issues such as inadequate technological infrastructure, financial constraints, and resistance to change as significant challenges to AI adoption in the public manufacturing sector, while Kumar et al. [64] similarly noted policy and regulatory gaps, infrastructure deficiencies, and stakeholder resistance in the public distribution system. Additionally, Chatterjee et al. [63] identified data privacy, security risks, and regulatory compliance as key challenges, which are also among the identified *CCs*. Two identified *CCs*, namely high implementation costs and a lack of technical skills and knowledge, are also consistent with findings in the water sector, as reported by Fu et al. [70].

Secondly, none of these *CCs* are related to social concerns such as job security, differing from the findings by Nam [88], which highlight the association between job insecurity and technology usage. This discrepancy may reflect the current state of the organization in the case study, which has yet to fully implement AI technologies. At this stage, its focus may be more on overcoming initial barriers—such as technical and financial constraints—rather than addressing secondary or long-term social concerns like privacy and workforce implications. As AI adoption progresses, these social challenges may become more significant.

The identified *CC*s were structured into a hierarchical graphical model depicted in Figure 2, which comprised four levels. At the lowest level, we found a lack of technical skills and knowledge (*CC* 7), limited ready-to-use AI solutions (*CC* 9), and incompetent water infrastructure (*CC* 10). Addressing these *CCs* should be conducted first for any effort to implement AI. Among these CCs, CC 9 represents an external challenge that necessitates substantial investment in research and development (R&D). This is evident in the ISM model (Figure 2), which depicts a direct relationship between *CC* 9 and the high cost of R&D (*CC* 3) at Level 3.

According to the ISM model, a lack of technical skills and knowledge (*CC* 7) directly affects two other *CCs* at Level 3 of the ISM model: high R&D cost (*CC* 3) and the bias problem (*CC* 5). The insufficiency of skills and knowledge (*CC* 7) directly contributes to the emergence of algorithm biases (*CC* 5) due to flawed statistical assumptions, inappropriate model selection, incorrect data preprocessing techniques, and other factors. *CC* 7 can also lead to inefficient R&D processes, resulting in longer development cycles, reliance on trial-and-error approaches, and an increased likelihood of errors or the need for rework. These inefficiencies contribute to higher R&D costs (*CC* 3). Additionally, organizations lacking internal expertise may have to seek external consultants or contractors, leading to additional expenses. Given that the development of AI solutions necessitates an investment in R&D, it is evident that a high R&D cost (*CC* 3) will lead to a high cost of AI implementation (*CC* 1), located at the highest level of the ISM model.

Regarding the other internal challenge at the lowest level, namely incompetent infrastructure (*CC* 10), the ISM model indicates that this challenge directly affects privacy and data security concerns (*CC* 2) and the lack of a data management system (*CC* 6), both positioned at Level 2 of the model. The relationships between *CC* 2, *CC* 10, and *CC* 6 can be described as follows: Incompetent infrastructure refers to inadequate or outdated hardware, network capabilities, and security measures within the organization's technological setup. This inadequacy can result in insufficient security measures, updates, and regulation compliance, impeding data protection and privacy. Moreover, it hinders effective data storage, processing, and advanced analytics capabilities, limiting the extraction of meaningful insights from data. Therefore, addressing *CC* 10 will contribute to addressing *CC* 2 and *CC* 6.

Additionally, Figure 2 demonstrates that *CC* 6 directly influences trust and transparency-related issues (*CC* 5). Furthermore, *CC* 5 has a bidirectional relationship with another CC_i at the same level, namely responsibility and accountability (*CC* 8). The relationship between *CC* 6, *CC* 5, and *CC* 8 can be explained as follows: The absence of proper data management increases the risk of incomplete or inaccurate information, eroding trust in the data and their insights. Transparency is compromised when stakeholders cannot rely on the reliability and completeness of the data. The lack of a suitable system also obstructs visibility, making establishing clear accountability and demonstrating transparency in data management practices challenging. This lack of visibility raises concerns about data governance, compliance, and adherence to ethical standards, thereby undermining trust. Addressing trust and transparency issues (*CC* 5) ultimately promotes responsibility and accountability in AI systems (*CC* 8). Transparent and explainable AI systems enable developers and organizations to better understand their behavior, identify biases or unintended consequences, and adopt responsible and accountable AI practices.

One advantage of utilizing fuzzy MICMAC analysis is categorizing variables into four groups (autonomous, dependent, independent, and linkage). However, the driving-dependence power diagram in Figure 3 illustrates that no linkage *CC*s exist for implementing AI, but there are autonomous, dependent, and independent *CCs*.

Found in the upper-right quadrant of the driving-dependence power diagram presented in Figure 3, autonomous *CC*s exhibit a weak driving power and a weak level of dependency. *CCs* 5, 6, and 9 fall into this group. Resolving any challenge within this group will have minimal or no impact on addressing *CCs* in other groups. Likewise, tackling *CC*s from other groups will insignificantly influence the resolution of these specific *CCs*.

Situated in the lower-right quadrant of the driving-dependence power diagram (Figure 3), dependent *CC*s demonstrate weak driving power and substantial dependency. Resolving any challenge within this group will have minimal or no impact on addressing *CCs* in other groups. Conversely, tackling *CC*s from other groups will significantly influence the resolution of these specific *CCs*. *CC* 1, *CC* 3, *CC* 4, and *CC* 8 belong to this particular group.

Located in the upper-left quadrant of the driving-dependence power diagram (Figure 3), independent *CCs* display a strong driving power and a weak level of dependency. Resolving *CC*s from other groups will have minimal or no impact on the resolution of these specific *CCs*. However, addressing any challenge within this group will help to resolve other *CCs* in the other groups. *CC* 2, *CC* 7, and *CC* 10 are included in this group.

5. Addressing the Most *CCs*

CCs placed at the lowest level of the ISM model and/or those classified as independent CCs should be prioritized in any AI implementation efforts. As depicted in Figures 2 and 3, these *CCs* are privacy and data security concerns (*CC* 2), limited ready-to-use AI solutions (*CC* 9), a lack of technical skills and knowledge (*CC* 7), and incompetent water infrastructure (*CC* 10). *CC* 2 is an independent *CC*, while *CC* 9 is located at the lowest level of the ISM model. *CC* 7 and *CC* 10 are located at the lowest level of the ISM model and are categorized as independent *CCs*. This section offers recommendations to tackle these most pressing *CCs*.

5.1. Lack of Technical Skills and Knowledge

To tackle the challenge of a lack of technical skills and knowledge, adopting an approach involving offering training programs, creating cross-functional teams, and leveraging external resources is recommended.

The programs must be customized to different levels of expertise and cater to technical and non-technical professionals. These programs might cover providing employees with AI fundamentals, programming languages, machine learning algorithms, and data analysis techniques. Such programs can be offered in collaboration with educational institutions or AI training providers. Alongside investing in comprehensive upskilling and training initiatives, addressing the deficiency in technical expertise requires cooperation between various departments within the organization to bridge the knowledge gap and gain a comprehensive understanding of AI implementation. This cooperation can be achieved by creating cross-functional teams comprising individuals with diverse skills, such as data scientists, domain experts, and IT professionals. To streamline the process and offer practical guidance for team composition and management, thereby enhancing the chances of success, it is recommended to consider team role frameworks, such as the one prescribed by Belbin [89].

Moreover, organizations can leverage external resources to bridge the technical skills gap. Collaborative partnerships with technology vendors, start-ups, and research institutions can provide access to expertise, tools, and pre-built AI solutions. Engaging consultants and experts in AI implementation can offer valuable guidance and accelerate the learning curve. Furthermore, participation in industry networks, conferences, and online communities can facilitate knowledge exchange and keep organizations updated on AI advancements.

5.2. Limited Ready-to-Use AI Solutions

The preferred approach has been an in-house development because AI solutions implemented in a specific industry may not easily translate to other sectors [90]. This method offers several advantages, such as tailoring solutions to precise requirements, maintaining control over the process, and adapting to evolving organizational needs. Nevertheless, developing AI solutions from scratch is time-consuming and intricate, involving extensive research, development, and testing. Therefore, it is advisable to begin by building upon existing applications described in the literature and adopting established patents. This approach minimizes the risk of failure and enhances the likelihood of successful AI solutions. Furthermore, adopting existing patents ensures that the developed AI solutions fall within the bounds of intellectual property rights, mitigating potential legal challenges that may arise from reinventing patented technologies.

Irrespective of whether the development process starts from scratch or builds on reported applications, it is essential to consider the concept of AI-based teammates in human–AI collaboration in developing AI solutions. This notion emphasizes integrating AI systems as interactive and cooperative partners working in synergy with humans, combining human intelligence with AI capabilities [91].

The framework for assessing benefits and risks proposed by Richards et al. [88] can be adopted for the responsible and safe deployment of AI solutions. This framework outlines three stages for deploying AI solutions: theoretical screening, proof of concept, and practical scale-up. Theoretical screening focuses on identifying potential areas within a water system where AI interventions could be beneficial, along with selecting the most suitable AI system to deliver these benefits. Proof of concept involves testing the AI system prototype in a lab setting and assessing its performance in a real-world scenario that closely mirrors the intended environment. Finally, practical scale-up includes monitoring the actual usage of the AI system to ensure that it aligns with its intended purpose and evaluating its performance to confirm it meets expected standards.

5.3. Incompetent Water Infrastructure

While AI can benefit the water sector regardless of infrastructure updates, an updated water infrastructure provides a solid foundation for effective AI integration [90]. As Richards et al. [92] highlighted, the effectiveness of AI is contingent on the quality of the systems it is integrated with and the individuals overseeing its development. An upgraded water infrastructure facilitates enhanced data collection, compatibility with AI platforms, extensive sensor coverage, and improved automation capabilities.

Conducting a thorough assessment to identify areas of weakness and inefficiency is the first step towards upgrading the existing water infrastructure. Accordingly, a plan should be made to target infrastructure for repairs or upgrades so that the updated water infrastructures can incorporate modern technologies, ensuring compatibility and interoperability with AI platforms and applications. These allow smooth integration and seamless communication between AI systems and the existing infrastructure, enhancing the effectiveness of AI algorithms. To succeed, achieving infrastructure improvements requires collaboration among water utility stakeholders, including technology providers, government agencies, and funding institutions. Moreover, establishing public–private partnerships can facilitate the exchange of expertise, resources, and funding opportunities. Such collaborative efforts drive innovation, promote knowledge sharing, and accelerate the implementation of AI in water infrastructure.

5.4. Privacy and Data Security Concerns

AI systems are vulnerable to various types of attacks, such as manipulating input data or exploiting weaknesses in their algorithms. These attacks can have serious consequences, including altering results or compromising users' privacy and security [93]. Addressing these privacy challenges is crucial, and safeguarding personal information should be a top priority. Alongside data protection, it is essential to consider the regulatory and ethical frameworks that guide the responsible use of AI, particularly regarding privacy and security [63].

Security concerns around AI systems are also increasing due to the risks they face during implementation. Vulnerabilities can arise from factors such as weak AI algorithms, the manipulation of training data, poor system design, or flaws in their execution. These risks may lead to adversarial attacks, biased models, information leaks, or harmful decision-making. Therefore, ensuring robust security for AI systems is essential to prevent these issues.

In relation to privacy and data security, the developed ISM model has shown a direct link between incompetent water infrastructure and these concerns. Improving water infrastructure can also help to address privacy and security issues. These challenges can be better managed by investing in strong infrastructure that uses industry-standard security protocols, regular updates, and strict privacy regulations. Furthermore, implementing a comprehensive framework with key elements such as risk assessments, data protection policies, AI model security, monitoring, transparency, and continuous improvement is recommended. One example of such a framework is developed by Villegas-Ch and García-Ortiz [61]. However, these efforts need to be supported at the government level, as effective regulation plays a crucial role in instigating necessary actions, controlling adherence to high standards, and protecting users' rights. The UAE government has already taken steps in this direction by issuing several laws and regulations to safeguard personal data and ensure the secure use of digital technologies [94]. These regulations not only set essential benchmarks but also foster an environment where privacy and security are prioritized, demonstrating the importance of regulatory support in achieving secure and user-centered digital infrastructure.

6. Conclusions

This study examined the *CCs* that impede the implementation of AI in the water sector, utilizing a prominent service utility organization in the UAE as a case study. The employed approach of ISM–fuzzy MICMAC analysis provided a comprehensive framework for identifying and classifying *CCs* that impede the implementation of AI in this sector. Initially, the *CCs* were identified based on the existing literature and subsequently refined by a panel of experts to a list of ten perceived *CCs*. The same panel of experts then assessed the relationships between each pair of *CCs*. Using the ISM technique, a four-level hierarchical graph was established to represent these relationships. The binary relationships were later converted into weights as part of the fuzzy MICMAC analysis, facilitating the classification of *CCs* into groups.

Visualizing the relationships among the *CCs* through the developed ISM model offers significant advantages, as graphical feedback is faster and more comprehensive than numerical feedback when dealing with complex multidimensional information. As a result, decision-makers can visualize the interconnections between *CCs*, gaining insights into how addressing one challenge can directly and indirectly impact other linked *CCs*. This understanding proves invaluable in formulating an efficient and effective AI implementation strategy. The strategy should prioritize efforts to address four specific *CCs*, namely the lack of technical skills and knowledge, the limited availability of ready-to-use AI solutions, incompetent water infrastructure, and privacy and data security concerns. These *CCs* have been identified based on their classification by fuzzy MICMAC as independent *CCs* and/or their positioning at the lowest level of the ISM model. A comprehensive discussion on addressing these *CCs* has been presented.

The findings and recommendations of this study not only address the specific challenges of implementing AI in the water supply sector within the UAE but also offer a roadmap for broader sectoral advancement. By focusing on overcoming initial technical and infrastructural challenges, investing in human capital, and ensuring ethical and secure AI integration, the water sector can navigate the complexities of AI adoption, enhancing efficiency, sustainability, and service quality. Addressing challenges such as skill gaps and outdated infrastructure could yield long-term social and economic benefits, particularly in regions prioritizing AI as part of their national strategies, like the UAE. However, it is important to recognize that AI's transformative potential in the water sector hinges on the successful execution of strategic and coordinated efforts involving key stakeholders, including government agencies, technology providers, water utility organizations, and academic institutions, to overcome the multifaceted challenges associated with its implementation.

As with most research endeavors, recognizing and acknowledging the limitations of this study is essential. One limitation is that this case study focused on a single organization in the UAE, meaning that the findings may primarily apply to organizations operating in the UAE or in similar environments. Additionally, the study only used dependence power and driving power metrics to identify the most critical *CCs*. Future research could explore other supplementary metrics to provide a more comprehensive understanding of the identified *CCs*. Another limitation lies in the reliance of the ISM–fuzzy MICMAC approach on expert input to define and establish relationships among the challenges, introducing a degree of subjectivity. Moreover, this study did not examine the associations between *CCs* and specific organizational characteristics, such as size or ownership type. Further research could investigate how these characteristics impact the identified *CCs*, offering additional insights. This study also emphasized the importance of regulatory support in addressing privacy and data security concerns. Future work could focus on fostering collaborations between governments and organizations to create global benchmarks for secure and ethical AI adoption. Such benchmarks could ensure alignment with international standards and promote the widespread, responsible implementation of AI technologies across diverse sectors.

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