

# Empirical Insights and Technical Stakeholder Perspectives: AI for Effective Decision-Making in South Africa's Water Management Sector

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## Abstract

South Africa's water management sector faces escalating challenges from climate change, population growth, and fragmented governance. This study investigates strategic stakeholder perceptions of artificial intelligence (AI) as a tool for effective decision-making, focusing on five thematic domains: Key Challenges in Water Management (CWM), Impacts of Climate Change and Population Growth (ICCPG), AI for Effective Decision-Making (AIEDM), Recommendations for Improving AI Tools (RIAIT), and Data Privacy and Security (DPS). A structured digital questionnaire using a five-point Likert scale was administered to thirty-five professionals across engineering, planning, policy, and civil society sectors. Purposive sampling ensured strategic-level representation. Quantitative analysis using SPSS v30 included descriptive statistics, reliability testing ( $\alpha = 0.929$ ), Pearson correlations, and multiple regression modelling. Findings reveal significant relationships between ICCPG and all predictor domains, with CWM ( $r = 0.756$ ) and DPS ( $r = 0.697$ ) emerging as the strongest predictors. Technically trained stakeholders demonstrated high alignment between climate/data concerns and systemic water challenges. The relatively lower influence of AIEDM and RIAIT suggests cautious optimism toward AI, tempered by concerns around implementation feasibility and ethical safeguards. To address the "black-box" problem, which is the difficulty in understanding or explaining how AI systems arrive at their decisions, particularly deep learning, the study advocates for the integration of Explainable AI (XAI) to enhance transparency and stakeholder trust. These insights align with South Africa's National Water Act and Water and Sanitation Master Plan, underscoring the need for integrated governance, digital literacy, and inclusive stakeholder engagement to support AI-enabled water resilience.

**Keywords:** Artificial Intelligence (AI) · Water Resource Management · Climate Change · Stakeholder Perceptions · Explainable AI (XAI) · Decision-Making · Data Privacy

## 1. Introduction

South Africa continues to face a severe water crisis, driven by the increasing demands of rapid urbanisation, ageing infrastructure in critical institutions, and the growing impacts of climate variability. Despite policy ambitions for data-driven decision-making, reliance on outdated rainfall and hydrological datasets remains a significant barrier (DWS, 2023). Water security remains foundational to the country's socio-economic development, underpinning agriculture, industry, and human well-being. However, with an average annual rainfall of 465 mm, significantly below the global average of 689 mm, and increasing variability (Wolski, 2018), the nation is experiencing more frequent droughts

and extreme weather events that disrupt supply systems and exacerbate vulnerabilities. These challenges are compounded by outdated hydrological datasets and fragmented data management systems, which undermine effective water resource planning (DWS, 2023). The consequences are visible in recurring drought conditions in metropolitan centres such as Cape Town (Brühl & Visser, 2021) and Johannesburg, and in flood-prone regions of KwaZulu-Natal (Lemanski, 2020). Artificial Intelligence (AI) offers transformative potential to analyse complex datasets, forecast water availability, and support infrastructure planning (Radanliev, 2024; Sham et al., 2025).

Globally, AI has been leveraged in water management to enhance predictive capacity, operational efficiency, and resource allocation. Applications include forecasting rainfall patterns, modelling river basin flows, detecting leaks in distribution networks, and optimising agricultural irrigation systems (Abiodun et al., 2018). Countries such as India and Brazil have adopted AI-enabled water allocation platforms that integrate satellite imagery with participatory governance frameworks, while Kenya's AI-driven rural water monitoring systems have achieved operational cost reductions of up to 40% (Ndubuisi, 2025). In contrast, South Africa's adoption of AI in the water sector has been slower, with policy ambition outpacing institutional uptake. AI applications remain limited despite promising pilots, e.g., Eskom's hydrological modelling, smart metering in Cape Town, and AI-based irrigation forecasting by the Agricultural Research Council. Barriers include institutional fragmentation, limited technical capacity, and the absence of a coordinated AI policy framework. These constraints threaten progress toward the National Development Plan (NDP) 2030 and Sustainable Development Goal (SDG) 6 targets.

The slow adoption of AI raises critical questions about the readiness of water authorities, municipalities, and policymakers to harness digital tools in addressing outdated datasets, climate-related risks, and governance inefficiencies. This study is framed by Technology Acceptance Theory (Silva, 2015), which emphasises perceived usefulness and trust as key drivers of adoption, and multi-level governance theory (Hooghe & Marks, 2001), which highlights the role of institutional coordination. AI adoption is positioned as a socio-technical process shaped by governance structures, stakeholder confidence, and ethical safeguards. Aligned with the NDP 2030 and SDGs, particularly SDG 6 (clean water and sanitation) and SDG 14 (life below water), this research offers empirical insights to advance inclusive, AI-enabled water governance. Potential applications include analysing long-term climate trends for drought preparedness, integrating diverse datasets for comprehensive water balance assessments, and supporting scenario-based planning for infrastructure and environmental resilience.

As of 2025, the sector faces a dual challenge: intensifying water scarcity and inadequate adoption of advanced decision-support tools/technologies. The persistence of outdated datasets and fragmented monitoring systems undermines planners' capacity to anticipate and respond to emerging risks. While AI offers robust analytical tools to identify trends, optimise allocations, and forecast shortages, its deployment remains sporadic and poorly documented. High-profile crises, such as Cape Town's "Day Zero" water shortage in 2017–2018, have demonstrated the consequences of delayed action, while rural communities in provinces such as Limpopo, Eastern Cape, and KwaZulu-Natal remain disproportionately affected due to inconsistent access to potable water, dependence on unreliable natural sources, and poorly maintained infrastructure (Lemanski, 2020). This study addresses gaps in empirical understanding of stakeholder trust, readiness, and perceptions of AI in water governance. It contributes to the literature by linking technical optimism with ethical and institutional considerations, and by proposing Explainable AI (XAI) as a mechanism for transparent, policy-aligned AI deployment.

## **2. Methodology**

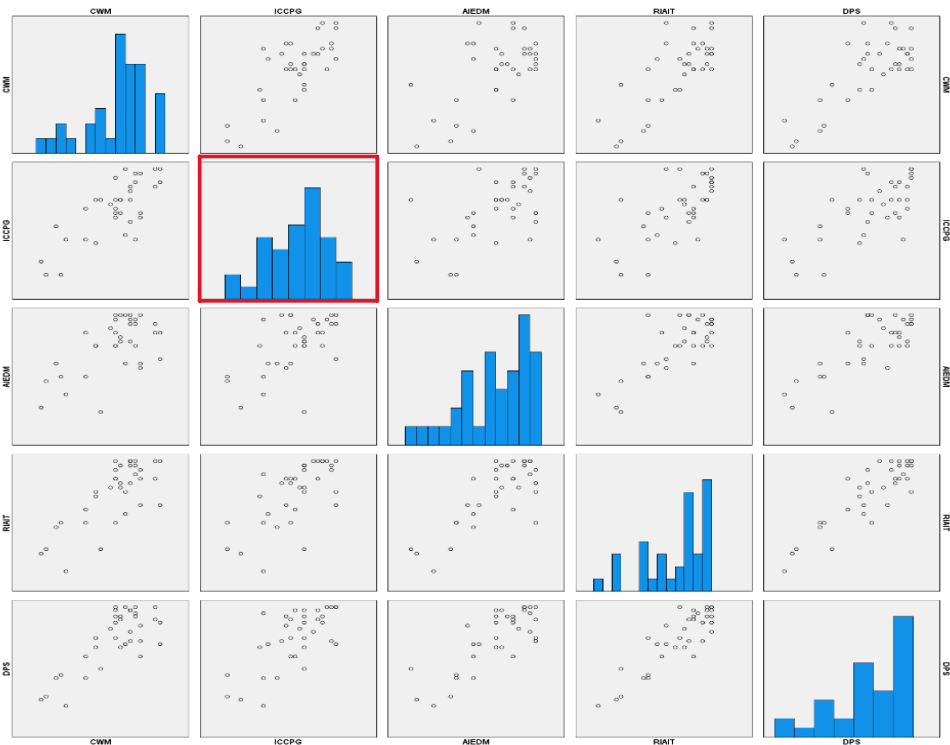
### **2.1 Study Area Description and Study Materials**

This study was conducted within the framework of South Africa's evolving water management sector, with a geographic focus on provinces experiencing acute climate-related stress and infrastructure constraints, particularly Gauteng. Gauteng exemplifies the national challenges around water resource resilience, exacerbated by rapid urbanisation and environmental variability. These persistent challenges include chronic water scarcity, ageing or inefficient infrastructure, uneven distribution of water services, and the intensifying impacts of climate variability on supply and demand. AI adoption in the sector remains limited to a few pilot initiatives, despite clear alignment with national policy frameworks (e.g.

the National Water Act) and global targets like SDG 6 (clean water and sanitation). A diverse cross-section of stakeholders participated in the research, including civil engineers, municipal water planners, policy advisors, and civil society actors involved in water governance and infrastructure decision-making across metropolitan municipalities, regional water boards, and rural water supply schemes. The Pair Plot of Thematic Variables Related to ICCPG and the Distribution of ICCPG Scores with Normal Curve Overlay is illustrated in the figs. 1 and 2.

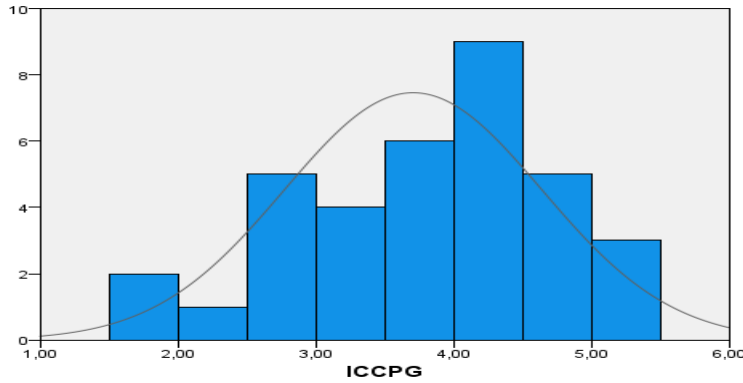
## 2.2 Instrument Design and Data Collection

Primary data for this study were collected through a structured online questionnaire administered via Google Forms. The survey targeted professionals across the water management value chain, with a particular focus on members of the South African Institution of Civil Engineering (SAICE), the South African Council for the Project and Construction Management Professions (SACPCMP), and the Engineering Council of South Africa (ECSA). This approach ensured that the sample included experienced practitioners from diverse organisational contexts, ranging from government agencies and private water utilities to community-based organisations. In total, thirty-five valid responses were obtained, representing a wide range of regional perspectives, including respondents from climate-stressed areas such as Gauteng. While modest in size, the sample is appropriate given the limited pool of professionals operating at the strategic level of South Africa’s water management sector.



*Fig. 11: Pair Plot of Thematic Variables Related to ICCPG*

Note: Diagonal histograms show variable distributions; off-diagonal scatter plots reveal potential correlations and clustering patterns relevant to stakeholder perceptions.



*Fig 22: Distribution of ICCPG Scores with Normal Curve Overlay*

Note: The blue bars represent observed frequencies of ICCPG scores; the grey curve indicates the theoretical normal distribution. Visual inspection suggests approximate normality, supporting parametric analysis.

The questionnaire was designed to assess stakeholder perceptions of Artificial Intelligence (AI) adoption in water management through Likert-scale items, where 1 represented “Strongly Disagree” and 5 represented “Strongly Agree.” Survey items measured perceived benefits of AI, such as improved forecasting, smart irrigation systems, and resource planning; confidence in AI integration and institutional readiness; and perceived barriers, including data transparency concerns, workforce skills gaps, and governance challenges. These items were organised into five thematic domains: Key Challenges in Water Management, Impacts of Climate Change and Population Growth on Water Management, AI for Effective Decision-Making in Water Management, Recommendations for Improving AI Tools, and Data Privacy and Security.

Responses were securely exported to IBM SPSS Statistics (v30.0) for data coding and analysis. Descriptive statistics, including mean scores, standard deviations, and ranking of items, were generated to summarise trends across the thematic domains. Secondary sources, such as national policy documents, sector performance reports, and peer-reviewed literature on AI in water management, were also consulted to contextualise the findings and inform the interpretation of results. These materials supported the design of the questionnaire, ensuring that the research was grounded in both current industry challenges and emerging opportunities for AI integration.

**2.3 Methods and Techniques**

The study employed a quantitative, cross-sectional design to explore empirical relationships and stakeholder interpretations of AI integration in water management. Data analysis was performed, employing a combination of descriptive, reliability, correlational, and regression techniques. Cronbach’s alpha ( $\alpha = 0.929$ ) confirmed excellent reliability. Inter-item correlations ranged from 0.568 to 0.880. Descriptive statistics were calculated to summarise key distributional features of each thematic index, including means, standard deviations, minimums, and maximums. Histograms were generated to visually assess distribution normality across the five domains, as shown in Fig. 1.

**Table 11: Summary Item Statistics for ICCPG and Thematic Constructs**

*Summary Item Statistics*

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3,905	3,707	4,024	0,318	1,086	0,016	5
Inter-Item Correlations	0,726	0,568	0,880	0,311	1,548	0,008	5

A multiple linear regression analysis was performed to determine how well these factors collectively predicted ICCPG scores. Prior to analysis, standard regression assumptions, linearity, normality of residuals, and homoscedasticity were assessed and met. The model was statistically significant. Regression analysis revealed CWM and DPS as the strongest predictors of ICCPG perceptions. This has been illustrated in Table 1.

Graphical outputs were generated using SPSS Legacy Dialogues to enhance interpretability. These included bar charts for theme-level comparison, scatterplots to illustrate predictive relationships, and histograms to demonstrate distribution characteristics.

### 3. Results and Interpretation

#### 3.1 Thematic Distributions and Reliability

Descriptive statistics in Table revealed high mean scores across all indices, indicating strong stakeholder agreement on the relevance of AI and governance in water management:

**Table 2: Descriptive Statistics for ICCPG and Thematic Predictors**

*Descriptive Statistics*

	<b>N</b>	<b>Minimum</b>	<b>Maximum</b>	<b>Mean</b>	<b>Std. Deviation</b>
CWM	35	2,00	5,00	3,8536	0,79027
ICCPG	35	1,57	5,00	3,7069	0,93509
AIEDM	35	1,86	5,00	4,0245	0,87343
RIAIT	35	1,43	5,00	3,9551	0,99203
DPS	35	1,80	5,00	3,9829	0,92847
Valid N (listwise)	35				

The overall reliability of the instrument was confirmed with a Cronbach’s alpha of 0.929, indicating excellent internal consistency. Inter-item correlations ranged from 0.568 to 0.880, with the strongest associations observed between DPS and RIAIT ( $r = 0.880$ ), and between CWM and ICCPG ( $r = 0.756$ ). These results suggest conceptual coherence across themes and reinforce the interconnectedness of ethical governance and climate-responsive planning. These results have been included in Table and Table.

**Table 3: Reliability Statistics for Thematic Constructs in ICCPG Framework**

*Reliability Statistics*

<b>Cronbach's Alpha</b>	<b>Cronbach's Alpha Based on Standardised Items</b>	<b>N of Items</b>
0,929	0,930	5

**Table 4: Pearson Correlations Between ICCPG and Thematic Predictors**

*Inter-Item Correlation Matrix*

	<b>CWM</b>	<b>ICCPG</b>	<b>AIEDM</b>	<b>RIAIT</b>	<b>DPS</b>
CWM	1,000	0,756	0,604	0,754	0,776
ICCPG	0,756	1,000	0,568	0,664	0,697
AIEDM	0,604	0,568	1,000	0,782	0,778
RIAIT	0,754	0,664	0,782	1,000	0,880
DPS	0,776	0,697	0,778	0,880	1,000

#### 3.2 Correlational Dynamics

Pearson’s correlation coefficients demonstrated statistically significant relationships between ICCPG and all four predictor domains: CWM:  $r = 0.756$ , DPS:  $r = 0.697$ , RIAIT:  $r = 0.664$ , AIEDM:  $r = 0.568$ .

These findings indicate that stakeholder perceptions of climate and population pressures are most strongly influenced by systemic water management challenges and concerns around data governance. The moderate correlation with AIEDM suggests that while AI is viewed positively, its perceived impact is contingent on broader institutional readiness.

### 3.3 Predictive Modelling

A multiple linear regression analysis (Table) was conducted to assess the combined predictive power of CWM, AIEDM, RIAIT, and DPS on ICCPG scores. The model was statistically significant with  $F(4,30) = 11.445$  &  $p < 0.001$ , explaining 60.4% of the variance in ICCPG ( $R^2 = 0.604$ ). Standardised coefficients indicated that CWM ( $\beta = 0.42$ ,  $p < .001$ ) and DPS ( $\beta = 0.31$ ,  $p = .004$ ) were the strongest predictors, followed by AIEDM and RIAIT. The results are illustrated in Table.

**Table 5: Model Summary for Regression Predicting ICCPG Scores**

*Model Summary*

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0,777 <sup>a</sup>	0,604	0,551	0,62634

a. Predictors: (Constant), DPS, CWM, AIEDM, RIAIT

**Table 6: ANOVA Summary for Predictive Model of Climate and Population Impact Perceptions (ICCPG)**

*ANOVA<sup>a</sup>*

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	17,960	4	4,490	11,445	<,001 <sup>b</sup>
	Residual	11,769	30	0,392		
	Total	29,730	34			

a. Dependent Variable: ICCPG

b. Predictors: (Constant), DPS, CWM, AIEDM, RIAIT

As detailed in Table 7, CWM emerged as the strongest predictor, reinforcing the centrality of foundational water management challenges in shaping stakeholder views on climate and population impacts. DPS showed moderate influence, while AIEDM and RIAIT did not reach statistical significance, suggesting that technical optimism around AI is tempered by concerns about implementation feasibility and ethical safeguards.

**Table 2: Regression Coefficients for Predicting Stakeholder Perceptions of Climate and Population Impacts (ICCPG)**

*Coefficients<sup>a</sup>*

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	0,062	0,590		0,104	0,917		
	CWM	0,634	0,223	0,535	2,846	0,008	0,373	2,683
	AIEDM	0,062	0,208	0,058	0,298	0,768	0,350	2,854
	RIAIT	0,030	0,249	0,032	0,122	0,903	0,189	5,279
	DPS	0,210	0,274	0,208	0,763	0,451	0,178	5,629

a. Dependent Variable: ICCPG

### 3.4 Stakeholder Recognition of Water Management Challenges Relative to Data Privacy and Security Concerns

The bar chart in Fig illustrates how stakeholder perceptions of Data Privacy and Security (DPS) correlate with recognition of Challenges in Water Management (CWM) across employment positions. A clear positive trend emerges engineers and AI/IT professionals report higher CWM scores as DPS concern increases, indicating that those attuned to digital governance view water management as a complex, data-dependent challenge. Students in water-related fields show moderate alignment, while non-water students and intern graduates display weaker conceptual links. Intermediate patterns among sales engineers and contractors suggest context-driven variability. Overall, the data affirm that heightened DPS awareness, especially among technically trained stakeholders, strengthens recognition of systemic water issues. Embedding data governance literacy into water curricula and stakeholder engagement is essential for resilient, AI-enabled decision-making.

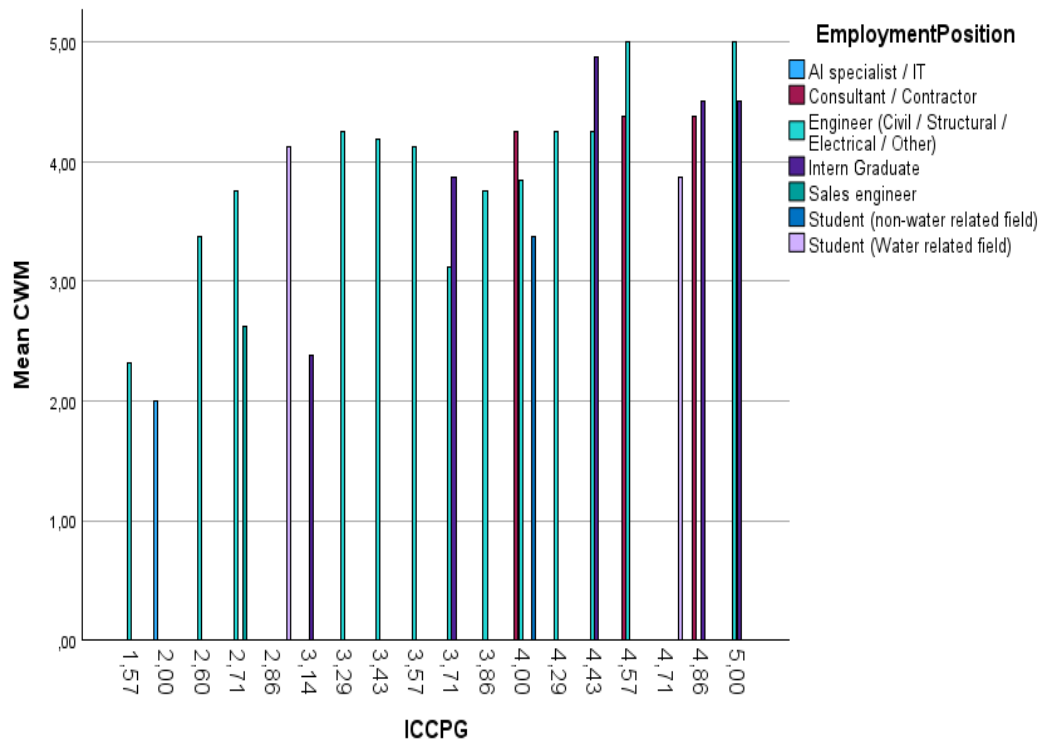


Fig. 3: Mean CWMI Scores by ICCPG Level Across Employment Positions

### 3.5 Stakeholder Perceptions of Water Management Challenges Relative to Climate and Population Impact Awareness

The bar chart in Fig. shows a clear positive association between perceived climate/population impacts (ICCPG) and recognition of water management challenges (CWM), across employment categories. Technically trained stakeholders, especially engineers and AI/IT professionals, report the highest CWM scores at elevated ICCPG levels, reflecting strong conceptual alignment between environmental stressors and systemic vulnerabilities. Water-related students show moderate awareness, while intern graduates and non-water students display weaker integration of climate-population dynamics with water governance. These findings reinforce CWM as the strongest predictor of ICCPG perceptions and highlight the need for targeted engagement strategies. Enhancing conceptual alignment among emerging professionals is vital for inclusive, AI-informed water decision-making.

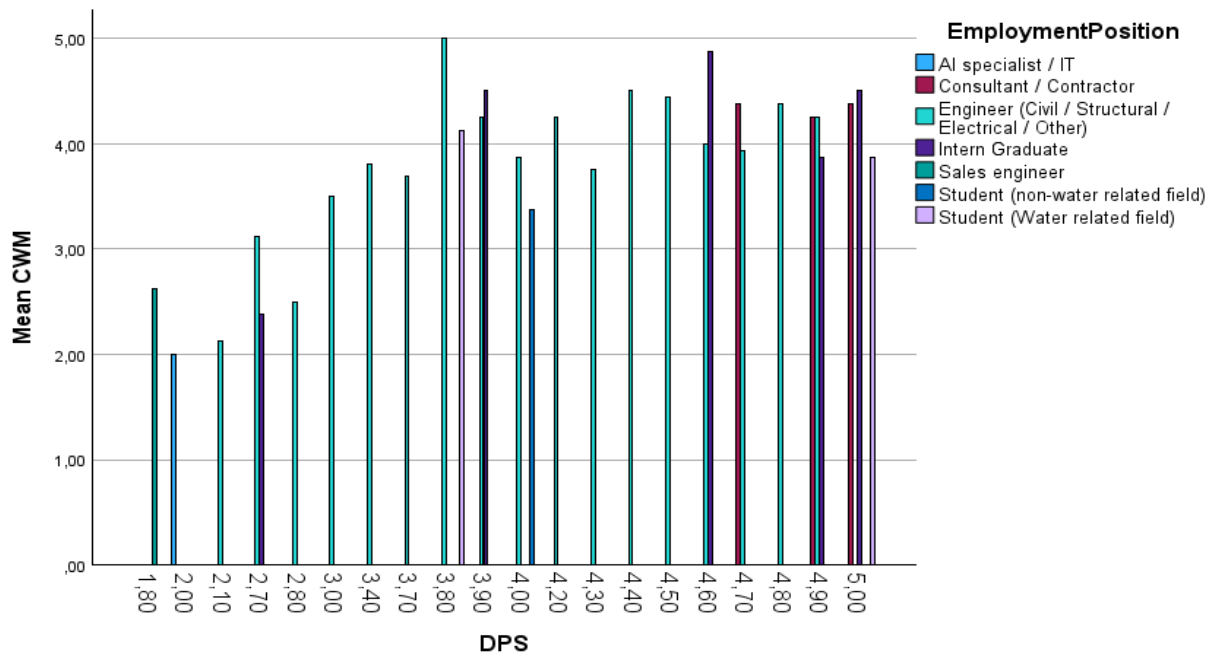


Fig. 4: Mean CWM Scores Across DPS Levels by Employment Position

### 3.6 Stakeholder Confidence in AI Capabilities and the Role of Explainable AI (XAI)

In

Table, Quantitative findings from 35 respondents reveal strong endorsement of AI’s role in enhancing water management across multiple dimensions. The highest-rated items include AI-driven data analysis (Mean = 4.14, Skewness = -1.240) and AI’s ability to predict water demand and supply trends (Mean = 4.09, Skewness = -1.267), indicating widespread belief in AI’s technical utility. Similarly, real-time monitoring of water supply and quality (Mean = 4.06) and AI-based early warning systems (Mean = 4.03) received high ratings, reflecting stakeholder confidence in AI’s responsiveness to environmental risks.

However, Explainable AI (XAI), while positively rated (Mean = 3.74), showed slightly lower consensus, with a broader spread (Std. Dev = 0.980) and less skewness (-0.437), suggesting that stakeholders value transparency but may require further exposure to XAI, as shown in Table and Fig. 5.

Table 8: Statistics description on the AI for effective decision making in water management

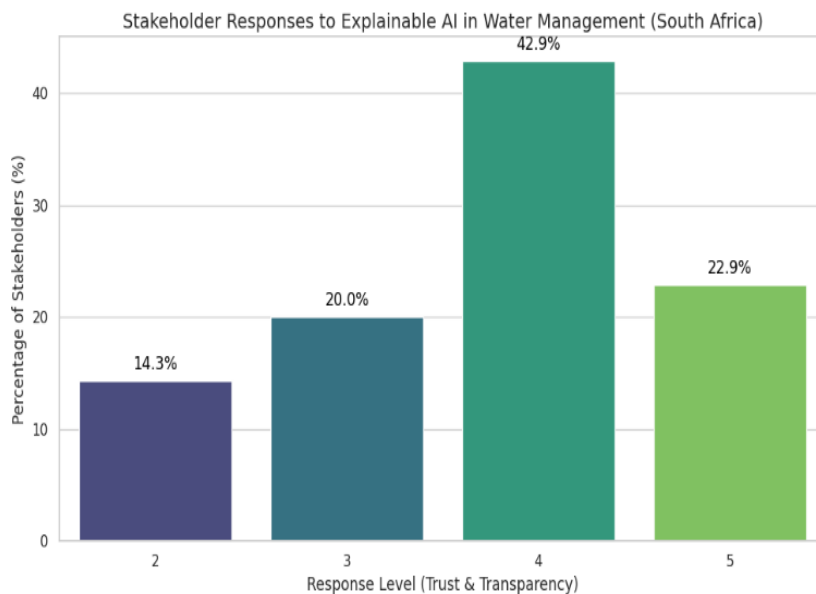
		AI-driven data analysis can improve the monitoring and management of water resources.	Real-time water supply and quality monitoring is possible with AI technologies.	AI can predict water demand and supply trends using historical and climate data.	Explainable AI (XAI) can enhance trust by making AI decisions more transparent.	AI-based early warning systems can improve preparedness for floods and droughts.	AI-driven optimization can schedule maintenance of treatment plants to minimise downtime.	Machine learning models can identify hidden patterns in water use data to inform policy interventions.	Standardising data formats and creating a centralised water database would improve AI efficiency.
N	Valid	35	35	35	35	35	35	35	35
	Missing	0	0	0	0	0	0	0	0

Mean	4,14	4,06	4,09	3,74	4,03	4,06	4,06	3,74
Std. Deviation	1,061	0,968	1,011	0,980	1,014	1,027	1,027	1,120
Skewness	-1,240	-0,531	-1,267	-0,437	-0,777	-0,810	-0,637	-0,521
Std. Error of Skewness	0,398	0,398	0,398	0,398	0,398	0,398	0,398	0,398
Percentiles	25	4,00	3,00	4,00	3,00	3,00	3,00	3,00
	50	4,00	4,00	4,00	4,00	4,00	4,00	4,00
	75	5,00	5,00	5,00	4,00	5,00	5,00	5,00

**Table 9: Explainable AI (XAI) can enhance trust by making AI decisions more transparent.**

Linkert 5 point scale	N	%
1	0	0,00%
2	5	14,3%
3	7	20,0%
4	15	42,9%
5	8	22,9%

N = number of responses



*Fig. 3: Explainable AI (XAI) can enhance trust by making AI decisions more transparent.*

## 4. Discussion

### 4.1 Climate, Data & AI: What Stakeholders Prioritize in Water Governance

Stakeholder responses reveal that concern about climate change and population growth (ICCPG), along with awareness of data privacy and security (DPS), are the strongest predictors of perceived challenges in water management (CWM). Stakeholders prioritise climate resilience and data governance over technical AI readiness. This reflects strategic maturity: AI is seen as a support tool, not a substitute for

ethical oversight. Comparative insights from Kenya and Brazil reinforce the need for socially embedded AI systems.

Technically trained professionals, especially engineers and AI/IT specialists, show the highest alignment, viewing water governance as a complex issue shaped by environmental stressors and digital accountability. Students in water-related fields show moderate awareness, while intern graduates and non-water students reflect weaker conceptual integration.

These findings suggest that effective AI adoption in South Africa’s water sector depends on pairing digital innovation with systemic reform and robust data governance. Comparative insights from Mthombeni et al. (2024) reinforce the need for transparent, collaborative, and socially embedded AI systems. Lower influence of AI-specific readiness indicators (AIEDM, RIAIT) points to strategic maturity: stakeholders see AI as a support tool, not a substitute for ethical oversight and inclusive planning. Visual outputs from the study have been optimised for use in policy briefs and stakeholder presentations, enabling clear, evidence-based engagement.

#### 4.2 Policy-Linked Integration of Explainable AI (XAI) in Water Management

The integration of Explainable Artificial Intelligence (XAI) into South Africa’s water management ecosystem offers a critical pathway toward transparent, accountable, and stakeholder-responsive decision-making. While conventional AI models have demonstrated predictive power in areas such as water demand forecasting, drought risk assessment, and smart irrigation, their “black box” nature often limits trust and uptake among policymakers, engineers, and community stakeholders. XAI addresses this gap by making algorithmic decisions interpretable, clarifying how inputs such as rainfall patterns, population growth, and infrastructure data lead to specific recommendations or alerts (Fawzy et al., 2023; Li et al., 2021)

In the South African context, where water governance is shaped by constitutional mandates for equity and participatory planning, XAI can enhance policy alignment by enabling traceable reasoning behind resource allocation, early warning systems, and infrastructure prioritisation. For instance, XAI-enabled dashboards could visually explain why a certain region is flagged for water stress, linking it to real-time sensor data and historical consumption trends. This not only supports informed consent and public buy-in but also strengthens interdepartmental coordination across municipalities, water boards, and climate agencies (Anderson et al., 2019; Lemanski, 2020).

Moreover, embedding XAI into AI-driven decision support systems aligns with South Africa’s National Water and Sanitation Master Plan, which emphasises data transparency, adaptive planning, and inclusive governance. By making AI outputs auditable and context-aware, XAI can help bridge the gap between technical innovation and policy implementation, ensuring that AI tools are not only effective but also ethically grounded and socially legitimate.

#### 4.3 Explainable AI (XAI) Integration

XAI offers a pathway to transparent, accountable decision-making. In South Africa’s participatory governance context, XAI can clarify how inputs (e.g., rainfall, infrastructure data) lead to specific recommendations.

Table shows that the proposed XAI dashboards would support traceable reasoning, informed consent, and interdepartmental coordination.

**Table 10: Proposed XAI Dashboard Components**

Component	Function	Data Sources
Real-Time Alerts	Flag water stress zones	Sensor networks, rainfall data
Decision Traceability	Explain allocation recommendations	Historical usage, population trends
Policy Alignment	Map outputs to NDP and SDG targets	National databases, planning tools
Stakeholder Interface	Enable feedback and scenario testing	Municipal platforms, civil society

Embedding XAI into decision-support systems aligns with the Water and Sanitation Master Plan and supports ethical, inclusive AI deployment.

The proposed framework for this study was structured into three sequential layers input, decision logic, and output designed to address the black-box limitations of conventional AI models, as shown in **Error! Reference source not found.** The input layer captures and visualises real-time and historical datasets, including hydrological and weather data, network and demand metrics, contextual variables such as land use and population, and data quality indicators. The decision logic layer processes these inputs through interpretable modelling techniques, combining data-driven variable weighting (e.g., SHAP values) with stakeholder-defined policy priorities (e.g., Analytic Hierarchy Process). This layer incorporates global explanations (overall feature importance) and local explanations (reason codes for each recommendation), supported by guardrails such as back testing, bias detection, and documented model cards. The output layer delivers transparent, human-readable recommendations via an interactive dashboard, showing top contributing factors, expected impacts, and confidence levels. Built-in governance features enable users to accept, modify, or reject AI recommendations with documented rationales, ensuring that decision-making remains accountable, auditable, and aligned with sector policies and regulatory frameworks.

## (XAI) Framework for Water-Management Decision Support



**Fig. 4: XAI Framework**

## 5. Conclusion

This study provides empirical evidence that stakeholder perceptions of water management in South Africa are strongly shaped by concerns about climate change, population growth, and data governance. Descriptive and inferential statistics confirm high levels of agreement across thematic domains, with Challenges in Water Management (CWM) and Data Privacy and Security (DPS) emerging as the most influential predictors of perceived climate and population impacts (ICCPG). The regression model explained 60.4% of the variance in ICCPG, reinforcing the centrality of foundational governance and ethical data practices in shaping stakeholder confidence.

Technically trained professionals, particularly engineers and AI/IT specialists, demonstrated the highest conceptual alignment, while students and early-career professionals reflected more variable understanding. These findings underscore the need for differentiated engagement strategies and curriculum reform to build capacity for inclusive, AI-informed decision-making.

Stakeholders expressed strong support for AI's technical capabilities, especially in predictive analytics, real-time monitoring, and early warning systems. However, the relatively lower consensus around Explainable AI (XAI) highlights the importance of transparency and interpretability in fostering trust. Embedding XAI into decision support systems aligns with South Africa's National Water and Sanitation Master Plan, offering a pathway to ethically grounded, socially legitimate, and policy-responsive AI deployment.

Overall, the study affirms that AI can play a transformative role in South Africa's water sector, but only if paired with systemic reform, stakeholder collaboration, and robust data governance.

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