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AI-DRIVEN ASSET MANAGEMENT FOR URBAN WATER INFRASTRUCTURE: IMPLICATIONS FOR CONSTRUCTION AND LIFECYCLE MANAGEMENT

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Abstract

The urban water system is at the heart of urban cities, providing public health, economic productivity and environmental sustainability. Planning, building, running and managing these systems in the long term need to be governed in a coordinated way across the technical, financial and institutional fields. The research investigates the intersection of artificial intelligence (AI) and infrastructure asset management in the context of urban water systems and the implications for construction planning and management of infrastructure lifecycle over time. A multi-layered governance framework is suggested and explained as a conceptual approach to improve the governance of the infrastructure asset management of urban water systems with AI. The framework places asset data ecosystems at the base of the digital integration and the development of digital intelligence with AI. Predictive analytics and digital monitoring outputs feed into lifecycle governance systems that drive the renewal prioritisation, cost optimisation and capital planning decisions. This involved conducting a systematic literature review of 22 peer-reviewed publications spanning the years 2015-2025, to synthesize current knowledge on the applications of AI, the governance issues that arise and implications for the lifecycle of AI. The results show that the integration of AI applications is mostly limited to the operational and maintenance stages, and is relatively rare in the earlier stages of lifecycle like planning, design and construction. This research brings a coherent analytical approach for digital infrastructure governance for future water systems, enabling precise and forward-looking management for long-term water systems' resilience.

Keywords*: Artificial Intelligence; Asset Management; Urban Water Infrastructure; Lifecycle Management; Digital Twins; Predictive Maintenance; Infrastructure Governance.*

1.0 INTRODUCTION

1.1 The Urban Water Infrastructure Is Key to the Strategic Imperative

Urban water infrastructure is a backbone of the stability of the domestic, industrial and environmental environment. But these complicated webs, which include the treatment plants, distribution networks and storage resources, are no longer just mechanical devices that need repairs every once in a while; they are fairly high-stakes strategic assets that enable public safety and economic continuity. The new operational to strategic governance is not a choice but a need due to the new pressures of the systems in which we live. At the moment the external factors are all interchangeable. The increasing numbers and growth of urban populations are putting unprecedented strain on capacities, and climate variability and the new demands for services on resilience of traditional service delivery. These are all contributing factors to the vulnerabilities of growing networks and the deferred maintenance. This convergence compels a reconfiguration of management practices, with the need to adopt a more proactive operational culture, which is increasingly proving to be too limited to deal with systemic risk.

1.2 What is a Good Asset Management System?

The development of asset management has been a journey of an activity that was once technical and isolated to a central part of the organization. This revolution in thinking recognises that value in the

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infrastructure is best optimised when technical operations are carefully aligned with financial plans and institutional strategy. However, today's integrated frameworks are proactive, and focus on lifecycle planning, prioritizing issues based on risk, and optimizing performance throughout the asset's life. The performance of infrastructure is now recognised as a poly-dimensional result and not just a mechanical performance. This performance is achieved through two different but related pillars, namely:

(1) Physical asset condition (material integrity, functional health of the asset itself)

(2) Maturity of organizational systems (sophistication of governance systems, systems for resource allocation, maintenance systems, etc., in relation to the functionality of the assets).

The biggest change along this line is the shift to risk-based prioritization. Instead of the traditional approach where long-term investments were made to guarantee the services over an extended period of time, with potentially inefficient emergency repairs in the event of failure, modern frameworks instead use failure probability and consequence severity to ensure that the investment made in the long term provides the services that are required in the event of failure (Nunes, Arraut, & Pimentel, 2023). This strategic fit allows limited capital to be put to use where it can have the greatest impact in managing systemic risk.

International standards, in particular ISO 55000, have played a key role in this professionalization by helping to "structure" the technical operations with the institutional strategy (da Silva & de Souza, 2022). ISO 55000, however, does not prescribe on how the operations should be executed. This leaves a gap in how the operational system works that only high fidelity data and smart systems can bridge, which are ones that can turn general principles into specific interventions that can actually be done.

1.3 Digital Transformation and the Edge of Artificial Intelligence

The water sector is in a radical digital transformation from siloed and manual databases to digital platforms. This transformation is changing both the way performance data is produced and used, providing improved situational awareness and a stronger operational overview (Grigg, 2025). The evolution of the combination of Supervisory Control and Data Acquisition (SCADA) systems, geospatial databases, and digital twins has shifted the utilities' focus from being reactive in their monitoring activities to being proactive in their modelling activities, where failure patterns are predicted before they even become an issue for their customers. Digital twins and smart monitoring systems offer virtual copies that are updated in real time with real-world data and can be used to simulate infrastructure operations and performance, helping to optimize infrastructure use and maintenance (Alourani et al., 2025; Voulvoulis et al., 2024). The need to move from data- to actionable intelligence-driven has been driven by AI, which has enabled the sector to shift from time-based maintenance to condition-based lifecycle management (Voipan, Voipan, & Barbu, 2025).

Students are expected to have the following research aim, scope, and objectives covered in their assignments. The study takes a global approach, by examining the management and governance aspects of the adoption of AI, instead of the technical engineering of the algorithms. The theme will be on digital intelligence changing the landscape of decision making and investment prioritization throughout the lifecycle.

Research Questions:

1) **RQ1**: What is the current status of the use of AI in supporting decision making for urban water asset management?

2) **RQ2**: How does AI contribute to the construction process through the utilization of various methods?

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3) **RQ3**: What are some of the organizational, governance, and related issues that impact the use of AI in infrastructure management?

4) **RQ4**: What are the gaps in the literature on integrated AI-driven lifecycle governance frameworks of water infrastructure?

2.0 METHODOLOGY

2.1 The Research Design Will Be a Literature Review

2.2 Philosophical foundations will be used for the literature review

However, the approach of this research is interpretive which assumes that knowledge is created in a social and contextual way. However, in the water industry, AI adoption is not just a technical occurrence, but a filtered one, through regulatory contexts, leadership approaches and the maturity of the organization. The methodology used is Inductive Reasoning which starts with the observation of the literature in detail to be able to draw a broader pattern in the form of thematic. The Research Strategy in this study includes Systematic Archival Literature Review (SALAR).The research strategy in this study is Systematic Archival Literature Review (SALAR). The general research approach was the systematic archival literature review. This allows for synthesis across the globe and across institutions, brings together a well-developed body of peer-reviewed scholarship, and helps to address synthesis-oriented goals aimed at articulating broader research gaps and governance trends and not assess a single site-specific implementation.

2.3 To Ensure Data Collection and Search Are Consistent and Repeatable, a Protocol Was Developed

The five databases used to collect primary data were chosen because of their specific role in supporting different areas of research in the field of civil engineering standards and infrastructure lifecycle knowledge:

1) **ASCE Library:** Civil engineering standards and lifecycle knowledge
2) **IEEE Xplore:** Technical : AI, sensor layers, and digital system architectures
3) **Science Direct, Scopus:** Interdisciplinary breadth across the field of environmental engineering and management
4) **Google Scholar:** High impact industry reports and emerging scholarly works, to ensure comprehensive coverage.

Artificial Intelligence AND Urban Water Infrastructure AND Predictive Maintenance OR Digital Twin OR Risk-based decision making AND Infrastructure Governance OR Lifecycle Management were used in the search queries.

2.4 Inclusion/Exclusion Criteria

A Systematic literature search was conducted for identifying relevant publications. The inclusion and exclusion criteria used to whitelist and blacklist the studies from the initial search results on the database are summarized in Table 1.

Table 1: Inclusion and Exclusion Criteria for Literature Selection

Criteria Category	Inclusion Parameters	Exclusion Parameters
Publication Type	Peer-reviewed journal articles; high-quality scholarly publications.	Non-scholarly opinion pieces; trade magazines.
Date Range	2015–2025	Publications prior to 2015.

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Subject Relevance	Direct focus on AI, digital twins, or predictive systems in water infrastructure.	Purely technical AI algorithm papers without governance or lifecycle context.
Methodology	Studies with clear, transparent methodological descriptions.	Articles with no identifiable research process or duplicates.

22 peer-reviewed studies were identified, having been selected by systematic screening according to these criteria, for in-depth thematic analysis.

2.5 The Three Stage Coding Process is the Second Step in Data Analysis

To ensure that conclusions are grounded in the source materials and not in subjective interpretations, a three-stage coding process was followed: Open Coding—identifying raw concepts from the 22 studies, including specific AI capabilities (e.g., neural networks for leak detection) or barriers to adoption; Axial Coding—grouping raw concepts into broader, related categories (e.g., 'Institutional Capability Readiness' or 'Risk-based Renewal Analytics'); and Selective Coding—final integration of categories to answer the main research questions. For every study, Structured Extraction Tables were used to record various aspects of the domain, type of AI application, and relevance to governance, so that all conclusions could be traced back to the source.

2.6 The Sampling Method and Validity Measures Were Described

Purposive sampling was used in the study as studies were carefully selected because of their potential to respond to the research problem. Theoretical Sufficiency (Saturation) was used for sample size determination, and the search was terminated when the new studies did not provide any new themes in relation to governance using AI. Validity and reliability were achieved by methods of

1. **(1) Triangulation:** findings replicated in different geographic and institutional locations in the 22 studies
2. **(2) Structured extraction:** the findings are presented in tables to prevent selective interpretation
3. **(3) Transparent criteria:** inclusion/exclusion parameters clearly defined to ensure the reproducibility of the findings.

3.0 RESULTS

A total of 22 publications were identified from the literature review and analysed. The next figures show distribution and characteristics of the studies reviewed.

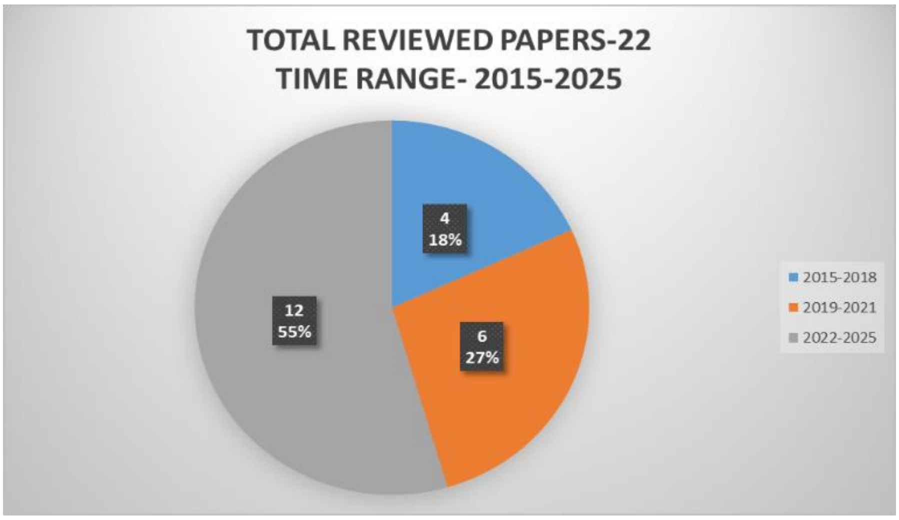

Figure 1: Thematic Distribution of Reviewed Literature by Primary Research Focus

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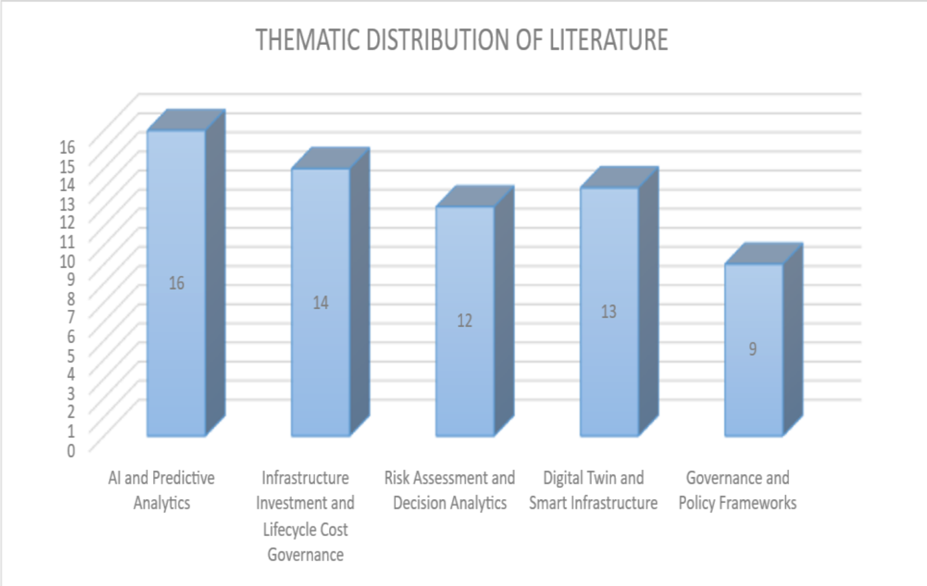

Figure 2: Geographic and Institutional Distribution of Reviewed Studies (N=22)

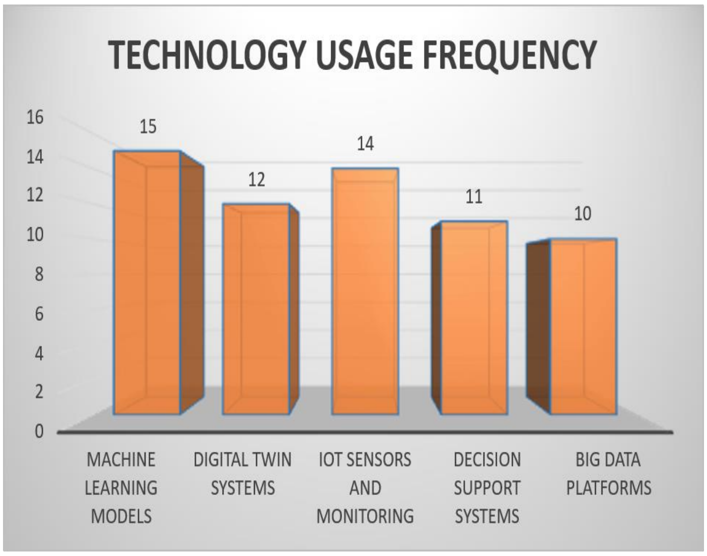

Figure 3: Infrastructure Lifecycle Phase Coverage in Reviewed Publications

3.1 State of the Art in the Use of AI in Asset Management (RQ1)

The results show that AI is mostly used in an operational context. Many technologies are utilized to enhance system performance and maintenance planning, including predictive maintenance models, infrastructure monitoring systems and data analytics platforms. These solutions empower infrastructure providers to shift from traditional reactive maintenance practices to proactively manage infrastructure using data-informed decisions, thus improving reliability and efficiency. Typical uses of AI include predictive modelling, or predicting failures, algorithms for detecting leaks and real-time monitoring through digital twins.

3.2 Acknowledges and Understands the Implications for Construction and Lifecycle Management (RQ2)

Results show that there is a great imbalance in the current research and practice. The use of AI applications is mainly focused on the operations and maintenance stage, rather than on the planning,

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design and construction phase. This means that the capabilities of AI to aid in the construction lifecycle management, such as asset strategy and project planning, are still not tapped. As a result, there are fewer chances to enhance lifecycle performance and cost efficiency by adopting a more integrated approach to digital.

3.3 Organizational and Governance Challenges (RQ3)

The study revealed that the institutional and managerial factors have a strong influence on the adoption of artificial intelligence. The issues are: (1) limited organizational preparedness; (2) data systems disintegration; (3) absence of interoperability and (4) inadequate integration of digital technologies in the traditional asset management processes. The results underscore the need for appropriate governance, data systems, and institutions to ensure the effective implementation of AI.

3.4 The research gaps in the current literature (RQ4)

The analysis showed that there are significant studies and applications of artificial intelligence in operations, but there are few studies that relate the applications of artificial intelligence to complete lifecycle governance and construction management systems. There has been little focus on the use of artificial intelligence to assist infrastructure planning, construction and delivery and asset management. This gap suggests that greater efforts are needed for more holistic solutions linking technological innovation to life cycle decision making. The proposed Conceptual Framework for AI-Driven Asset Management has been created. The Conceptual Framework for AI-Driven Asset Management has been proposed.

A conceptual framework is suggested which tries to operationalize AI-based lifecycle governance in five successive layers:

Some of the material listed below will be covered in this course. This course will cover some of the following material:

This layer provides the basic data sets and resources that form the core primary data repository for the development of asset intelligence, such as asset inventories, inspection records, hydraulic performance data sets, maintenance data sets, and geospatial infrastructure mapping systems.

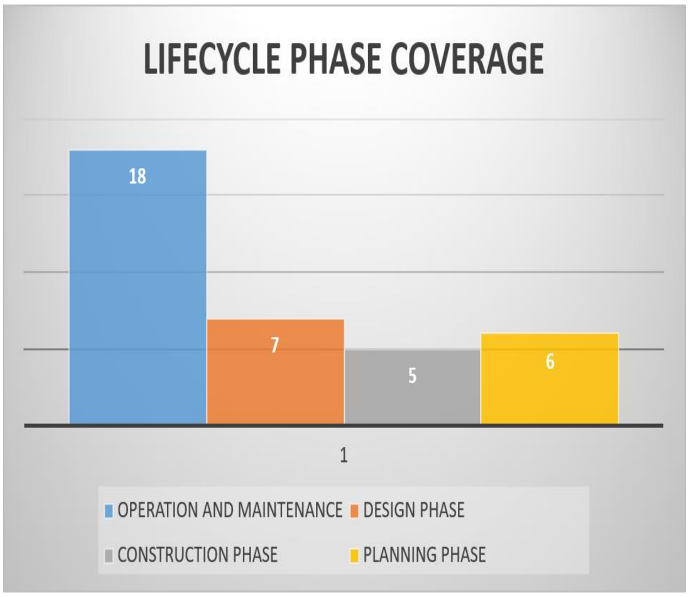

Figure 4: the Conceptual Framework for AI-Driven Lifecycle Asset Governance of Urban Water Infrastructure Has Been Developed

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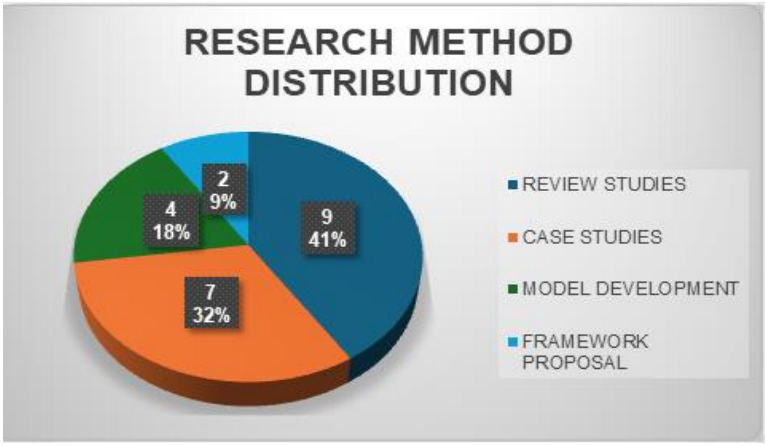

Figure 1: Research Method Distribution

4.0 PROPOSED CONCEPTUAL FRAMEWORK FOR AI-DRIVEN ASSET MANAGEMENT

A conceptual framework is proposed that operationalizes AI-driven lifecycle governance through five sequential layers. This foundational layer comprises asset inventories, inspection records, hydraulic performance datasets, maintenance histories, and geospatial infrastructure mapping systems that establish the primary data environment for asset intelligence development.

4.1 Framework Layer Descriptions

Layer 1: Infrastructure Asset Foundations

This foundational layer comprises asset inventories, inspection records, hydraulic performance datasets, maintenance histories, and geospatial infrastructure mapping systems that establish the primary data environment for asset intelligence development.

Layer 2: Data Integration and Digital Ecosystem

This layer consolidates infrastructure datasets within interoperable digital platforms. Technologies such as SCADA systems, IoT sensor networks, smart metering infrastructure, and cloud-based data repositories enable real-time monitoring, storage, and integration of asset performance information.

Layer 3: Ai-Enabled Intelligence Systems

At this stage, artificial intelligence transforms integrated infrastructure data into predictive and diagnostic insights. Machine learning models, digital twins, anomaly detection systems, and hydraulic forecasting tools support failure prediction, leakage detection, and performance simulation across asset networks.

Layer 4: Lifecycle Governance and Decision Systems

This governance layer translates AI-generated intelligence into strategic infrastructure actions. Renewal prioritization, lifecycle cost optimization, risk-based asset ranking, and capital investment planning decisions are formulated to enhance long-term service delivery and infrastructure sustainability.

Layer 5: Institutional and Organizational Moderators

The outer governance environment moderates the effectiveness of all preceding layers. Regulatory frameworks, financing capacity, workforce digital readiness, and governance maturity influence the adoption, scalability, and operationalization of AI-driven asset management systems. At this stage,

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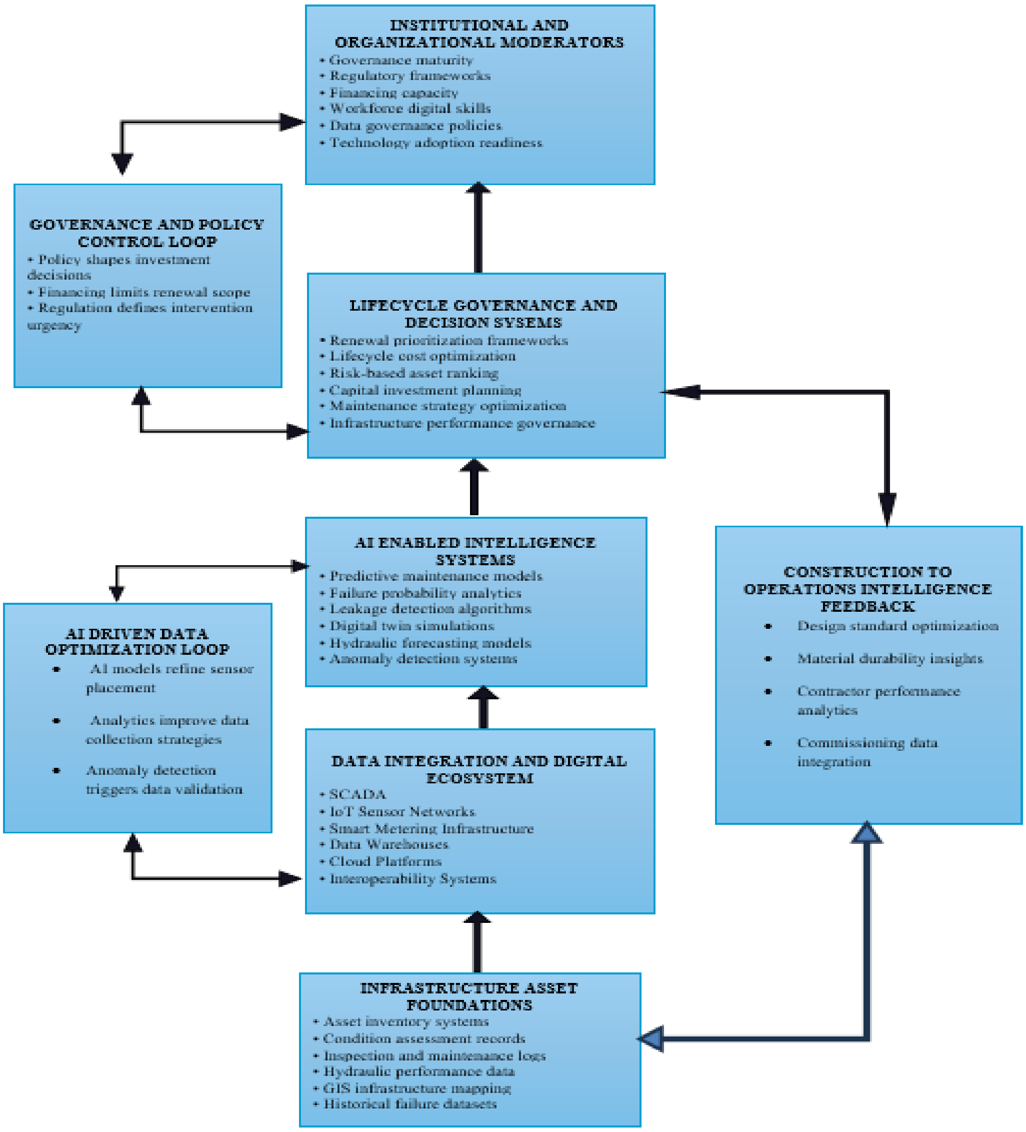

Figure 6: Conceptual Framework for AI Driven Lifecycle Asset Governance in Urban Water Infrastructure

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The proposed AI-driven lifecycle integrated framework is designed for direct implementation in construction and water infrastructure projects. It connects planning, design, construction, and operation through a continuous data loop, enabling informed decision-making at each stage.

5.0 APPLICATION IN PROJECT PLANNING

At the planning stage, the framework uses historical asset data, failure records, and environmental conditions to support data-driven feasibility analysis.

Practical use:

1) Predict high-risk zones for pipeline failures using historical leakage data
2) Optimize project prioritization based on risk and cost impact
3) Support investment decisions using AI-based cost-benefit analysis

Outcome: Better allocation of capital. Reduced uncertainty in early-stage decisions.

5.2 Application in Design Phase

The framework integrates predictive analytics into design development.

Practical use:

1) Select materials based on predicted lifecycle performance
2) Optimize pipe sizing and routing using demand and pressure simulations
3) Evaluate alternative designs using scenario-based AI models

Outcome: Designs become performance-driven, not assumption-based.

5.3 Application in Construction Phase

The framework enables forward application of operational intelligence during construction.

Practical use:

1) Use AI insights from existing assets to guide installation standards
2) Identify high-risk installation practices from historical defect data
3) Optimize construction scheduling using predictive risk models
4) Monitor quality using sensor-based validation and anomaly detection

Example: If AI shows that joint failures occur in specific soil conditions, construction teams adjust installation method before asset commissioning.

Outcome: Reduced defects. Improved build quality. Lower rework.

5.4 Application in Operation and Maintenance

The framework fully activates in the operational phase through real-time monitoring.

Practical use:

1) Predict failures using machine learning models
2) Detect leaks using pressure and flow anomalies
3) Optimize maintenance schedules using condition-based monitoring

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4) Reduce water loss through early detection systems

Outcome: Shift from reactive to predictive maintenance.

5.5 Digital Twin Enablement

The framework supports digital twin integration across lifecycle stages.

Practical use:

1) Create virtual replicas of infrastructure assets
2) Simulate performance under different scenarios
3) Test operational strategies before physical implementation

Outcome: Improved system resilience and planning accuracy.

5.6 Risk Assessment and Decision Support

AI-driven risk models are embedded across all phases.

Practical use:

1) Quantify failure probability and consequence
2) Rank assets for renewal and replacement
3) Support decision-making using multi-criteria analysis

Outcome: Transparent and objective decisions.

5.7 Governance and Management Integration

The framework aligns with asset management standards and organizational governance.

Practical use:

1) Define data ownership and accountability
2) Standardize decision workflows
3) Align with ISO 55000 principles

Outcome: Structured and auditable asset management practices.

6.0 IMPLEMENTATION ROADMAP

For practical deployment, organizations can follow a phased approach:

Phase 1: Data Collection and System Integration

Consolidate fragmented data sources into unified repositories. Establish interoperability protocols between legacy systems and modern platforms. Implement data governance frameworks defining ownership, quality standards, and access controls.

Phase 2: Pilot Implementation on Selected Assets

Test framework components on representative asset subsets before organization-wide deployment. Identify technical bottlenecks and governance gaps in controlled environments. Measure baseline performance metrics and establish benchmarks for success.

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Phase 3: AI Model Development and Validation

Train predictive models using historical and real-time data. Validate models against field observations to ensure accuracy and reliability. Iteratively refine algorithms based on performance feedback.

Phase 4: Full-Scale Deployment across Lifecycle

Expand framework implementation across all infrastructure assets and all lifecycle phases. Integrate AI outputs into routine decision-making workflows. Establish feedback loops for continuous model improvement.

Phase 5: Continuous Improvement and Feedback Integration

Monitor system performance and capture lessons learned. Update AI models with new data and refine governance processes. Foster organizational learning culture around digital asset management.

7.0 KEY BENEFITS IN PRACTICE

Implementation of the proposed AI-driven framework yields measurable benefits across multiple dimensions:

1) Reduction in asset failure rates through early prediction and preventive intervention
2) Improved construction quality through data-informed design and installation standards
3) Optimized capital and operational expenditure through risk-based prioritization
4) Enhanced decision transparency through objective, data-driven processes
5) Significant lifecycle cost savings from reduced emergency repairs and extended asset life
6) Increased infrastructure resilience to climate variability and aging-related challenges.

8.0 DISCUSSION

This systematic review reveals that while artificial intelligence has become increasingly prominent in operational asset management, significant integration gaps persist across the full infrastructure lifecycle. The concentration of AI applications in maintenance and operations phases, combined with limited integration into planning and design stages, represents a critical underutilization of predictive capabilities. This fragmentation reflects broader institutional silos that frequently separate infrastructure planning, construction delivery, and operations. The proposed five-layer framework addresses this fragmentation by positioning AI not as an isolated operational tool but as an integrated intelligence system spanning the complete asset lifecycle.

By embedding predictive analytics and performance insights into planning, design, and construction processes, utilities can achieve a fundamentally more efficient and resilient infrastructure management model. This integrated approach ensures that decisions made during capital planning and design are informed by actual asset performance patterns, thereby reducing costly design oversights and ensuring that renewal strategies align with predicted asset degradation trajectories.

However, the successful implementation of this framework requires more than technological deployment. Institutional barriers including data fragmentation, regulatory misalignment, workforce skill gaps, and organizational siloing must be systematically addressed. The research indicates that governance maturity, regulatory capacity, and financing readiness are critical moderators that determine whether technological capability translates into operational reality.

Forward-thinking utilities must therefore adopt a staged implementation approach that builds organizational and governance capacity in parallel with technological deployment. Future research

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should prioritize the development of implementation roadmaps that explicitly address the integration of AI systems into construction management and project delivery processes. Additionally, studies examining how operational intelligence can be effectively translated into capital planning and renewal strategies would provide critical practical guidance for practitioners.

9.0 CONCLUSION

This research examined the role of artificial intelligence in infrastructure asset management for urban water systems and evaluated its implications for construction lifecycle governance.

The research was guided by four research questions, and conclusions are presented in alignment with these questions. With respect to the first research question, which examined how artificial intelligence is used to support asset management decision-making, findings indicate that artificial intelligence is primarily applied in operational contexts. Technologies such as predictive maintenance models, infrastructure monitoring systems, and data analytics platforms are widely used to improve system performance and maintenance planning. These applications enable infrastructure organizations to move from reactive maintenance approaches toward more proactive and data-driven decision-making, thereby enhancing reliability and operational efficiency.

Regarding the second research question, which explored the implications of artificial intelligence for construction and lifecycle management, findings reveal a significant imbalance in current research and practice. Artificial intelligence applications are predominantly concentrated in the operations and maintenance phase, with limited integration into earlier lifecycle stages such as planning, design, and construction. This indicates that the potential of artificial intelligence to support construction lifecycle management—including project planning and long-term asset strategy—remains underutilized. Consequently, opportunities for improving lifecycle performance and cost efficiency through integrated digital approaches are not fully realized.

In relation to the third research question, which focused on organizational and governance challenges, the study found that adoption of artificial intelligence is strongly influenced by institutional and managerial factors. Key challenges include limited organizational readiness, fragmented data systems, lack of interoperability, and insufficient integration of digital technologies into existing asset management processes. These findings highlight that successful implementation of artificial intelligence requires not only technological capability but also effective governance structures, data management frameworks, and organizational capacity. The fourth research question addressed the identification of research gaps in the current literature. Analysis demonstrated that while substantial research exists on operational applications of artificial intelligence, there is a lack of studies that integrate these technologies within comprehensive lifecycle governance and construction management frameworks. Limited attention has been given to the role of artificial intelligence in supporting infrastructure planning, project delivery, and strategic asset management.

This gap indicates a need for more integrated approaches that connect technological innovation with lifecycle decision-making. Based on these findings, this research contributes to knowledge by proposing an integrated framework that links artificial intelligence capabilities with infrastructure lifecycle asset governance. The framework addresses the identified gap by providing a structured approach for incorporating data-driven technologies into construction management and asset management practices. It emphasizes the importance of aligning artificial intelligence applications with lifecycle governance processes to support coordinated and informed decision-making.

The key contribution of this work lies in bridging the persistent disconnect between technological innovation and organizational practice. While artificial intelligence offers unprecedented capabilities for infrastructure performance prediction and optimization, these capabilities remain underutilized

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due to institutional fragmentation and governance barriers. By positioning AI within a comprehensive lifecycle framework and explicitly addressing organizational requirements, this research provides a practical pathway for utilities to transition from reactive, asset-specific interventions toward proactive, system-wide governance models. As urban water infrastructure faces mounting pressures from climate uncertainty, aging asset bases, and rising service expectations, the integration of artificial intelligence with comprehensive lifecycle governance represents an essential step toward long-term infrastructure resilience. Future implementations of this framework will require sustained commitment to organizational transformation, governance alignment, and workforce development alongside technological deployment.

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