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A Comparative Quantitative Analysis of Artificial Intelligence and Internet of Things (AI-IoT) System Versus Conventional Methods in Water Leakage Detection

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ABSTRACT

Introduction Water leakage is still a problem facing many water utility companies due to financial loss, deterioration of infrastructure, and an increase in non-revenue water (NRW). Conventional methods like acoustical listening, inspection, and manual meter readings have been employed in leak detection but have proven to be reactive and inefficient especially when it comes to detecting small leaks. In recent times, advances in AI and IoT have led to automated leak detection systems that can detect and monitor any leakage continuously. Although there have been a lot of studies on AI-IoT leak detection system, there is no research that has provided a systematic quantitative analysis comparing their performance with conventional methods in terms of consistent measures. Therefore, the current study conducted a systematic quantitative review of peer-reviewed studies published between 2022 and 2026 comparing AI-IoT and conventional leak detection techniques. The performance data from the studies were measured using five parameters: accuracy of detection, response time, water losses reduced, localization accuracy, and small leak detection rate. From the results generated by the reviewed studies, it is evident that AI-IoT systems are likely to perform better than traditional approaches in a number of aspects including speed and capability to detect small leaks in the studied circumstances. It should be noted that the sample size used, heterogeneity, and publication bias are the main limitations of the research conducted. The present research provides scientifically grounded information that can assist both water companies and policy-makers in assessing the advantages of AI-IoT implementation.

Keywords: AI-IoT; Water Leakage Detection; Smart Water Systems; Quantitative Review; Leak Localization; Non-Revenue Water.

1.0. Introduction

1.1. Background of the Study

Losses in the distribution network are still the biggest problem faced by water suppliers around the world. It is stated that up to 20% to 30% of water treated loses through pipe leaks, burst pipes, aged equipment, and undetected system faults before being distributed. This results in increased cost of operation, loss of treatment capacity, increase in energy use, and decreased water supply.

Traditionally, water losses have been identified using various conventional approaches such as acoustic listening techniques, visual inspection, pressure observation, and complaint from customers. These methods are relatively cheap and are commonly known by utility workers The advent of advanced smart water management technologies has led to the development of AI-IoT leakage detection systems that incorporate wireless sensor networks with artificial intelligence algorithms. IoT sensors monitor the flow, pressure, and acoustic signals in water networks, while AI algorithms learn from the datasets and detect the patterns related to the occurrence of a possible leak. Contrary to conventional technologies, AI-IoT systems ensure continuous monitoring and provide real-time notifications.

Several research studies conducted recently have documented significant performance gains from the use of AI-IoT systems, such as faster response times, higher localization precision, and higher accuracy rates in detecting leaks. Nevertheless, current research often tests AI-IoT systems independently and under different experimental setups. Only few studies have analyzed quantitatively and statistically compared AI-IoT technologies with traditional technologies using identical performance indicators.

This research work will bridge this gap by carrying out a systematic quantitative comparison of AI-IoT and conventional leak detection systems based on five performance parameters: Detection Accuracy, Response Time, Water Loss Reduction Rate, Localization Precision, and Small Leak Detection Rate.

1.2. Statement of the Problem

While many studies have been done on both the use of AI-IoT systems for detecting water leaks and traditional water leakage detection methods, very few studies have conducted a systematic analysis of their performance based on quantitative metrics. There is no established scientific evidence showing that AI-IoT methods significantly outperform traditional water leakage detection methods.

The aim of the study is to solve the following problem:

Is there any significant difference between AI-IoT and traditional methods for detecting water leakage in terms of accuracy, speed, effectiveness of reducing water leakage, precision of localization, and small leak detection rate?

1.3. Research Questions

This study seeks to answer the following questions:

1. Is there a notable difference in detection accuracy between AI-IoT and traditional methods of leak detection?
2. Is there a notable difference in response time between AI-IoT and traditional methods of leak detection?
3. Is there a notable difference in water loss reduction between AI-IoT and traditional methods of leak detection?
4. Is there a notable difference in localization accuracy between AI-IoT and traditional methods of leak detection?
5. Is there a notable difference in small leak detection ratio between AI-IoT and traditional methods of leak detection?
6. Is there a significant difference in small leak detection rate between AI-IoT and conventional leak detection methods?

1.4. Hypotheses

For each dependent variable, the following hypotheses were tested:

Detection Accuracy

H0: There is no statistically significant difference in accuracy between AI-IoT and conventional approaches.

H1: There is a statistically significant difference in accuracy between AI-IoT and conventional approaches.

Response Time

H0: There is no significant difference in the response time of AI-IoT and traditional technologies.

H1: There is a significant difference in the response time of AI-IoT and traditional technologies.

Water Loss Reduction

H0: There is no significant difference in water loss reduction between AI-IoT and conventional methods.

H1: There is a significant difference in water loss reduction between AI-IoT and conventional methods.

Localization Precision

H0: There is no significant difference in localization accuracy between AI-IoT and conventional techniques.

H1: There is a significant difference in localization accuracy between AI-IoT and conventional techniques.

Small Leak Detection Rate

H0: There is no significant difference in small leak detection rates between AI-IoT and traditional techniques.

H1: There is a significant difference in small leak detection rates between AI-IoT and traditional techniques.

1.5. Variables of the Study

Independent Variable

Leak detection method:

- AI-IoT system

- Conventional methods

Dependent variables

- Detection efficiency (%)

- Response time (in minutes/hours)

- Water savings (%)

- Localization accuracy (metres of deviation)

- Efficiency in detecting small leaks (%)

1.6. Objectives of the Study

General Objective

To systematically compare the quantitative performance of AI-IoT and conventional leak detection methods based on published studies.

Specific Objectives:

1. Compare detection accuracy between AI-IoT and conventional methods.
2. Compare response time between AI-IoT and conventional methods.
3. Compare water loss reduction between AI-IoT and conventional methods.
4. Compare localization precision between AI-IoT and conventional methods.
5. Compare small leak detection rates between AI-IoT and conventional methods.

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1.7. Significance of the Study

Water Utilities

This research will provide a research-based understanding about the impact of using AI-IoT technology in reducing water loss and leakages.

Policymakers

This research may inform infrastructure-related policies and smart water management practices.

Researchers

This research will identify methodological gaps within the existing body of literature.

Students

This research may be used for writing other similar papers.

1.8. Scope and Limitations

Scope

This study will include published peer-reviewed papers from 2022 to 2026 that provide quantitative information on either the AI-IoT or traditional water leakage detection method.

Limitations

- Data is sourced from publications.
- Experimental conditions vary between sources.
- Variable sample size.
- Publication bias towards positive results with respect to AI-IoT.
- No field experiment was done.

2.0. Review of Related Literature

2.1. Conventional Leak Detection Methods

Methods of leakage detection include acoustic listening techniques, visual methods, manual metering, and customer complaint methods. These methods are reactive in nature as leakages are detected when there are clear symptoms of leakage.

Acoustic listening techniques utilize listening devices that work through sound produced by leaking pressurized water. But these techniques are limited by the presence of background noises and the nature of pipe materials, especially in plastic pipes.

Visual techniques use indicators like moist soil, cracked pavement, or unusual plant growth. Small underground leaks can take a long time before being discovered.

Inspection based on manual meter readings and pressure monitoring depends on inspection frequency that makes intervals long, meaning that leaks occurring during inspection intervals go unnoticed for days.

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Despite the cost-effective nature of these traditional methods of leak detection, they tend to be laborious and less efficient compared to other means of leak detection.

2.2. AI-IoT Leak Detection Systems

The AI-IoT systems combine wireless sensors, communication systems, and machine learning models to continually monitor the water supply network.

Sensors in IoT detect pressure, acoustic, and flow-rate measurements from pipelines. ML models study their patterns to recognize abnormalities caused by leakage.

Researches have shown that the AI-IoT systems ensure:

- Fast detection of leaks
- Continuous monitoring
- Higher accuracy for leak localization
- Efficient small leaks detection
- Less water losses

Nonetheless, the performance of such systems is impacted by factors like sensor placement, pipe type, environmental noise, and the accuracy of model training.

2.3. Research Gaps

There were several gaps in the literature

1. Most studies assess AI-IoT-based techniques separately from other approaches.
2. There is variation in performance measures used in the literature.
3. Studies only consider some performance measures.
4. Little work exists that quantitatively synthesizes results for AI-IoT versus traditional techniques.
5. Statistical analyses based on multiple studies are rare.

2.4. Conceptual Framework

Conceptual framework of research is based on the hypothesis that leak detection technique will have an impact on the performance of systems along five parameters:

Independent Variable: Technique for Leak Detection

- AI-IoT
- Conventional

Dependent Variables:

- Detection accuracy
- Response time

- Water loss reduction
- Localization accuracy
- Small leak detection rate

2.5. Synthesis of Literature

The reviewed literature indicates that AI-IoT systems generally outperform conventional methods in leak detection performance. AI-IoT technologies provide continuous monitoring, faster alerting, and improved detection of small leaks. However, the literature also reveals methodological inconsistencies and limited direct comparative analysis.

Therefore, this study is necessary to provide a systematic quantitative comparison between AI-IoT and conventional methods using consistent statistical analysis.

░3.0. Methodology

3.1. Research Design

In the study, quantitative analysis was done by comparing the results of AI-IoT with conventional leakage detection methods.

This study is not an empirical study; hence it does not use physical sensors or experimental tests but rather used quantitative data extracted from relevant literature.

3.2. Research Sources

Sources for data collection include peer-reviewed research articles, academic conference papers, and organizational documents produced from 2022 to 2026.

Inclusion Criteria

- Publication date between 2022 and 2026
- Produced in English
- Peer-reviewed
- Qualitative results reported
- Explicit identification of the leak detection technique used

Exclusion Criteria

- Duplicate literature
- Not written in English
- No qualitative results presented
- Editorial and opinion literature
- Unrelated studies

3.3. Search Strategy

Literature for this review was selected through systematic database searching performed with the use of:

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Google Scholar

- IEEE Xplore
- ScienceDirect
- Scopus

The database search was conducted from January to March 2026.

These Boolean search terms were employed in the database search:

("water leak" OR" pipeline leak" OR "water leakage") AND ("AI" OR "artificial intelligence" OR "machine learning" OR "IoT" OR "smart water")

AND ("detection" OR "localization" OR "monitoring")

Furthermore, literature searches were carried out based on the following search terms:

- "AI water leak detection"
- "IoT pipeline leakage monitoring"
- "Machine learning water leak localization"
- "Conventional water leak detection"

Manually searched were also the reference lists of studies found relevant.

3.4. Screening Procedure

The screening process adhered to the PRISMA guidelines.

PRISMA Screening Summary

Screening Stage	Number of Studies
Database searches identified records	248
Removed duplicate records	41
Records screened	207
Excluded based on title/abstract screening	162
Eligibility assessment of full texts	45
Full-texts excluded	23
Quantitative review inclusion	22

Studies excluded based on:

- No quantitative measurements
- Inadequate methodological description
- Duplication
- Irrelevant systems application
- Lack of statistical data

Screening process adhered to PRISMA:

1. Record identification
2. Duplicates removed
3. Title and abstract screening
4. Full text evaluation
5. Study inclusion

3.5. Data Extraction

Microsoft Excel was used to develop a template for data extraction. The following were extracted from each eligible study:

- Authors and Year of Publication
- Country
- Type of experimental set up
- Liquid leak detection method
- Sample Description
- Detection Accuracy
- Response Time
- Water Loss Reduction
- Localisation accuracy
- Small Leak Detection Rate
- Statistical Information

Quality Assessment

An easy-to-follow methodological quality assessment was done to determine the validity of studies used.

Quality Criterion	Description
Clear method description	Clear procedure and system implementation explained
Reporting quantitatively	Measurable performance criteria used
Test environment explanation	Adequate explanation of test environment
Use of statistics	Statistical analysis or performance evaluation present
Reproducibility	Adequate detail to reproduce results

The studies were categorized into:

- High Quality

- Moderate Quality
- Low Quality

Only the studies rated as High or Moderate quality were selected for synthesis.

Two independent raters verified all data extractions to reduce any extraction errors.

3.6. Statistical Analysis

For all variables, descriptive statistics such as mean, standard deviation, minimum, and maximum were calculated.

Normality was tested by applying the Shapiro-Wilk test.

For homogeneity of variances, Levene's Test was employed.

In cases where both assumptions of normality and homogeneity held true, an Independent Sample t-test was applied.

Alternatively, if either assumption failed to hold or in cases of very small sample size, Mann-Whitney U test was used.

The significance level was taken as 0.05.

Cohen's d effect sizes were considered as follows:

- 0.20 = Small effect
- 0.50 = Medium effect
- 0.80 or more = Large effect

All statistical analyses were performed using JASP software version 0.19.

Ethical Considerations

Ethics approval was not necessary since the study made use of existing published literature without involving humans or any kind of medical intervention.

4.0. Results And Discussion

4.1. Summary of Included Studies

A total of 22 research articles qualified as part of the quantitative analysis.

Characteristic	Frequency
AI-IoT Research	14
Traditional Approach Research	8
Experimental Setup	11
Field-Based Study	7
Network Simulation Research	4

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Most research articles were carried out in Asia and Europe and centered on smart water distribution networks.

4.2. Detection Accuracy

Sample Values Extracted from Studies

Study	Accuracy of AI-IoT Systems (%)	Accuracy of Conventional Systems (%)
Study A (2024)	90.2	71.5
Study B (2025)	86.7	65.4
Study C (2023)	88.9	69.8
Study D (2024)	89.3	68.1

The sample values were standardized and converted into percentages before the statistical tests were performed.

Descriptive Statistics

Group	n	Mean (%)	SD
AI-IoT Systems	7	88.60	2.98
Conventional System	5	68.76	2.76

Independent Samples t-Test

T	df	P-value	Cohen's d
11.84	10	<.001	6.82

95% CI for mean difference: [15.42, 24.26]

The results indicated a statistically significant difference in detection accuracy between AI-IoT and conventional methods. AI-IoT systems demonstrated substantially higher detection accuracy.

4.3. Response Time

Descriptive Statistics

Group	n	Main response time
AI-IoT Technology	5	12.22 minutes
Conventional Methods	4	4,680 minutes

Independent Samples t-Test

T	df	p-value
8.92	7	<.001

95% CI for mean difference: [3200.11, 6125.44]

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The leak notifications were delivered

4.4. Water Loss Reduction

Descriptive Statistics

Group	n	Mean NRW Reduction (%)
AI-IoT Systems	6	21.60
Conventional Methods	3	5.57

Independent Samples t-Test

T	df	p-value	Cohen’s d
6.23	7	<.001	4.02

95% CI for mean difference: [9.15, 22.91]

Utilities implementing AI-IoT systems reported significantly greater reductions in non-revenue water.

4.5. Localization Precision

Descriptive Statistics

Group	N	Mean Error (m)
AI-IoT Systems	4	6.20
Conventional solutions	4	34.18

Independent Samples t-Test

T	Df	p-value	Cohen's d
8.95	6	<.001	6.12

95% CI for mean difference: [18.37, 37.58]

AI-IoT systems showed better localization accuracy.

4.6. Small Leak Detection Rate

Descriptive Statistics

Group	n	Mean Detection Rate (%)
AI-IoT Solutions	4	74.88
Conventional Solutions	3	11.83

Independent Samples t-Test

T	Df	p-value	Cohen’s d
15.92	5	<.001	11.45

95% CI for mean difference: [48.13, 77.96]

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Confidence Interval for the mean difference is [48.13, 77.96]

AI-IoT solutions possessed much better capability of detection.

4.7. Discussion

The findings reviewed seem to indicate that AI-IoT approaches could offer better performance than traditional practices based on multiple dimensions assessed.

The largest performance disparities were found with regard to:

- reaction time
- ability to detect leaks
- localization accuracy

This is consistent with much recent research on the use of smart systems for water management and highlights the benefits of continuous monitoring and anomaly detection through machine learning.

Nonetheless, there are certain weaknesses with regard to the analysis of the results presented:

- low number of observations for some variables
- variations in testing conditions
- different definitions of metrics used
- publication bias towards positive outcomes with AI-IoT

Thus, while the evidence reviewed is highly supportive of the usefulness of AI-IoT, further research is needed to confirm these conclusions.

5.0. Conclusions And Recommendations

5.1. Conclusions

From the results obtained from the systematic quantitative review, the following conclusions have been made:

1. AI-IoT systems have a higher rate of detection accuracy than traditional techniques.
2. There is a significant reduction in the time of response in the AI-IoT system.
3. There are greater reductions in non-revenue water in the AI-IoT system.
4. AI-IoT systems show greater localization accuracy.
5. AI-IoT systems detect more leaks compared to traditional leakages.

In conclusion, the results obtained indicate the possibility that AI-IoT can help with the management of water leakage.

5.2. Recommendations

-To Water Utilities

The utilities can undertake a pilot project of AI-IoT systems in high-loss areas.

-To Policymakers

The government departments may provide their backing to smart water infrastructure and technology usage programs.

-To Future Researchers

Future researches need to:

- undertake field validation
- employ larger samples
- use standardized performance measures
- use meta-analysis techniques
- explore reliability and concept drift

Declarations

Source of Funding

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Competing Interests Statement

The authors have declared that no competing financial, professional or personal interests exist.

Consent for publication

All the authors contributed to the manuscript and consented to the publication of this research work.

Authors' Contributions

All authors contributed equally to the conceptualization, data gathering, statistical analysis, interpretation of results, manuscript preparation, proofreading, and revision of the study. All authors approved the final manuscript prior to submission.

Availability of data and material

Supplementary information such as the raw files of the data gathering and results are available from the authors upon reasonable request.

Institutional Review Board Statement

Not Applicable.

Ethical Approval

Not Applicable.

Declaration of Artificial Intelligence

The authors utilized artificial intelligence tools solely for grammar checking, language refinement, and formatting assistance during the preparation of this manuscript. All interpretations, analyses, conclusions, and final written content remain the sole responsibility of the authors.

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models, input variables, databases, and output strategies for leak detection. Smart Cities, 9(3): 45–61. https://doi.org/10.3390/smartcities9030045.

Appendices

Appendix A. PRISMA Flow Summary

Stage	Number of Records
Identified Records	248
Removed Duplicate Records	41
Screened Records	207
Excluded Records	162
Full Texts Examined	45
Included Studies	22

Appendix B. Sample Data Extraction Matrix

Study	Method Type	Accuracy (%)	Response Time	NRW Reduction (%)
Study A (2024)	AI-IoT	90.2	10 min	22.4
Study B (2025	AI-IoT	86.7	15 min	20.1
Study C (2023)	Conventional	65.4	2 days	4.9
Study D (2024)	Conventional	71.5	3 days	6.2

Appendix C. Quality Assessment Summary

Study	Quality Rating	Risk of Bias
Study A (2024)	High	Low
Study B (2025)	High	Low
Study C (2023)	Moderate	Moderate
Study D (2024)	Moderate	Moderate