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# AI-POWERED DIGITAL TWIN ARCHITECTURE FOR SMART CITY INFRASTRUCTURE MANAGEMENT

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***Abstract***— *Rapid urbanization in developing countries places unprecedented pressure on urban infrastructure, yet AI-powered Digital Twin (AI-DT) systems have rarely been validated under the fragmented, bandwidth-constrained, and regulation-sensitive conditions of developing-country megacities. This study aims to design, implement, and evaluate an AI-DT architecture for smart city infrastructure management in the Jakarta Metropolitan Area, Indonesia, using a convergent mixed-methods design. The proposed four-layer architecture integrates multi-protocol IoT data acquisition, an Eclipse Ditto-based real-time synchronization engine, an AI analytics module combining Long Short-Term Memory (LSTM) and Gradient Boosting ensemble forecasting, Isolation Forest anomaly detection, and privacy-preserving Federated Learning, and a React.js/CesiumJS decision-support dashboard. The system was deployed on 47 sensor nodes across the transportation, energy, and water management domains for 12 months, accumulating 94.7 million sensor readings; performance was compared with a threshold-based SCADA baseline using Wilcoxon signed-rank tests, and 24 stakeholders were interviewed. The AI-DT system achieved an overall weighted anomaly detection F1-score of 0.891 compared with 0.692 for SCADA (a 28.8% relative improvement, $p < 0.001$), an energy consumption forecasting MAPE of 4.23%, a traffic flow forecasting RMSE of 187.4 veh/h, and 99.4% system uptime. The Federated Learning module converged in an average of 11 communication rounds while meeting the data sovereignty requirements of Government Regulation (PP) 71/2019. Stakeholder interviews confirmed improved failure anticipation but highlighted capacity-building and interoperability needs. The study provides an empirically validated AI-DT blueprint for smart city practitioners in Southeast Asia.*

***Keywords***: *Artificial intelligence, digital twin, federated learning, internet of things, smart city.*

## INTRODUCTION

Global urbanization is accelerating at an unprecedented pace. The United Nations projects that 68% of the world's population will reside in urban areas by 2050 [1]. In developing countries such as Indonesia, this trend is most visible in megacities like Jakarta, whose metropolitan population exceeds 34 million [2]. The resulting pressures on urban infrastructure, encompassing transportation networks, power grids, water distribution systems, and public services, demand transformative, data-driven management approaches that transcend conventional operational paradigms.

The Smart City concept has evolved from a techno-optimistic vision into an increasingly operationalizable framework, underpinned by the convergence of the Internet of Things (IoT), Big Data analytics, cloud computing, and Artificial Intelligence (AI) [3], [4]. Among emerging enabling technologies, the Digital Twin (DT), a virtual replica of a physical system continuously updated with real-time data, represents a particularly promising paradigm for urban management [5], [6]. Digital Twins provide city administrators with a dynamic, bidirectional interface between physical



infrastructure and its digital representation, enabling predictive maintenance, what-if scenario simulation, and evidence-based decision support [7], [8].

Despite growing academic interest, the deployment of AI-powered Digital Twin systems in smart city contexts within developing countries remains underexplored. Existing Digital Twin research has frequently examined well-established smart-city initiatives in technologically advanced contexts, where mature digital infrastructure and institutional capabilities facilitate large-scale implementation [9], [10]. This gap, however, is not merely geographical; it is substantive. Indonesian cities such as Jakarta exhibit heterogeneous infrastructure readiness across districts, rapid and informal urbanization patterns, chronic resource and budget constraints, and fragmented inter-agency governance, conditions that differ qualitatively from the centralized, well-resourced contexts in which prior AI-DT studies were conducted [11], [12]. Architectures validated under Singapore- or Helsinki-like conditions implicitly assume stable connectivity, mature data standards, and consolidated institutional authority, assumptions that do not hold in Jakarta's distributed, multi-agency, and bandwidth-constrained operating environment. Consequently, findings from advanced digital-economy contexts cannot be directly transposed to Indonesia, and a locally validated architecture and evaluation are required to determine whether AI-DT benefits persist under these structurally different conditions.

The Digital Twin paradigm, originally conceptualized in product lifecycle management [13], has undergone substantial conceptual expansion to encompass urban systems. Batty [14] highlighted the evolution of city-scale digital models, including City Information Models, as important foundations for representing and analysing the physical and informational dimensions of cities. Meanwhile, recent research has extended the Digital Twin concept toward urban-scale systems that integrate heterogeneous data, real-time monitoring, simulation, and analytical capabilities to support urban planning and decision-making [5]. Bibri et al. [15] conducted a comprehensive systematic review of 185 studies, highlighting the synergistic integration of artificial intelligence, AIoT, and urban Digital Twins to enhance data-driven urban planning, real-time analysis, and decision-making in sustainable smart cities.

However, the implementation of Urban Digital Twins remains particularly challenging in developing country contexts, Zali et al. [9] investigated the adoption of Urban Digital Twins in Iran and found that infrastructure limitations, organisational factors, policy and legislation, and technological capabilities significantly shape UDT development. These findings suggest that DT implementation cannot rely solely on technological capabilities but requires adaptation to local institutional, infrastructural, and socio-economic conditions. Furthermore, El-Agamy et al. [16] conducted a comprehensive bibliometric analysis of more than 4,220 publications on Digital Twins in smart cities, highlighting the increasing integration of IoT, machine learning, and data-driven analytics to support real-time monitoring and predictive urban management. Their findings also reveal persistent challenges related to data integration, interoperability, and the technological complexity of deploying Digital Twins at the city-scale.

AI methods applied to smart city infrastructure encompass supervised learning for demand forecasting, unsupervised learning for anomaly detection, and reinforcement learning for adaptive control [17]. In the energy domain, ensemble learning methods incorporating algorithms such as Random Forest, Gradient Boosting, and XGBoost have demonstrated strong performance in predicting building electricity consumption, highlighting the potential of ensemble approaches for capturing complex and nonlinear energy use patterns [18], [19]. In transportation systems, LSTM-based and other spatiotemporal deep learning models have increasingly been applied to urban traffic-flow prediction, with recent studies reporting improved predictive performance over conventional statistical approaches such as ARIMA [20].

Recent studies have demonstrated the applicability of Isolation Forest for anomaly detection in urban water infrastructure. Babela et al. [21] employed Isolation Forest to generate anomaly scores from heterogeneous data sources, including SCADA measurements, energy consumption, and environmental variables, in an urban water distribution network. Similarly, Cincotta et al. [22] applied Isolation Forest at the district-metered-area level to identify abnormal patterns associated with sensor failures, communication anomalies, bursts, and potential leakage events. These studies demonstrate the potential of unsupervised anomaly detection for supporting real-time monitoring and early-warning capabilities in smart urban water infrastructure.

Federated Learning (FL) enables collaborative model training across distributed edge nodes while keeping raw data at its original


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location. This decentralized learning paradigm is particularly relevant to smart city environments, where heterogeneous and privacy-sensitive data are generated across distributed infrastructures and organizational domains. By avoiding the direct centralization of raw data, FL can support privacy-preserving collaborative analytics while addressing data protection and regulatory requirements [23]. Wijaya et al. [24] provide a comprehensive review of FL challenges in IoT contexts. Hierarchical Federated Learning (HFL) has been investigated as an approach to improve the scalability and communication efficiency of federated learning in smart city IoT environments. By introducing intermediate edge-level aggregation before global model aggregation, HFL can reduce communication demands and better accommodate geographically distributed and resource-constrained sensing devices. Recent studies have demonstrated the applicability of hierarchical FL to smart city and IoT systems, particularly for addressing communication overhead, latency, and heterogeneous resource constraints [25].

Indonesia's national smart city agenda, articulated through the Gerakan Menuju 100 Smart City program, provides the policy backdrop for this research [26]. Studies based on SNI ISO 37122:2019 have emphasized the importance of systematic assessment of smart city readiness and the availability of standardized urban data for evaluating smart city performance, finding that digital infrastructure scores are improving, while real-time data integration and AI adoption remain underdeveloped [27]. At the organizational and governance level, Lestari et al. [28] proposed an Enterprise Architecture model for smart government implementation, emphasizing the importance of architectural alignment, integrated information systems, and interoperability in supporting coordinated digital public services. These requirements are particularly relevant to smart city environments, where heterogeneous information systems and services must exchange data to support integrated urban management. Wahyudi et al. [29] further assessed Jakarta Smart City (JSC) governance and identified fragmented data silos and limited predictive analytics as key limitations. Similarly, Tasa et al. [30] found that the implementation of the Jakarta Smart City concept has progressed across the dimensions of smart people, smart mobility, and smart governance, supported by digital society development, integrated public transportation, and ICT-enabled public services and governance policies. These challenges highlight the complexity of integrating heterogeneous urban services and data sources into a cohesive smart city ecosystem. From an AI governance perspective, Wijaya et al. [31] proposed an ambidextrous AI governance framework for smart cities that emphasizes balancing AI-driven innovation with IT governance, risk management, data security, and regulatory compliance. Collectively, these studies indicate that Indonesia's smart city development has progressed in digital infrastructure and service deployment, but challenges remain in achieving interoperable data ecosystems, integrated urban intelligence, predictive analytics, and effective governance of AI-enabled services.

The literature synthesis reveals three major scientific gaps that motivate this study. First, existing Digital Twin frameworks predominantly emphasize data visualization and real-time monitoring, while providing limited integration of predictive forecasting, anomaly detection, and adaptive learning within a unified architecture [16], [32]. Second, most reported implementations are domain-specific, focusing on a single infrastructure sector (e.g., transportation, energy, or flood management), thereby limiting interoperability and coordinated decision-making across heterogeneous urban systems [18], [19], [20], [21]. Third, although privacy-preserving machine learning has received increasing attention, the integration of Federated Learning into city-scale Digital Twin architectures remains insufficiently explored, particularly with respect to maintaining model performance while satisfying data governance and sovereignty requirements [23], [33]. To address these limitations, this study proposes and empirically validates a four-layer AI-powered Digital Twin architecture that integrates multi-domain IoT sensing, real-time Digital Twin synchronization, complementary AI analytics using LSTM and Isolation Forest, and Federated Learning within a unified decision-support framework.

From a methodological standpoint, prior AI-DT implementations have predominantly relied on either rule-based synchronization with single-model forecasting [7], [8] or centralized machine-learning pipelines that require raw sensor data to be transmitted to a central server [17], [34]. Both approaches present limitations that are particularly acute in the Indonesian setting: rule-based and single-model architectures lack the predictive robustness needed for the noisy, intermittent telemetry typical of heterogeneous legacy infrastructure, while centralized pipelines conflict with data-sovereignty requirements under PP 71/2019 and are vulnerable to the bandwidth constraints of a distributed, multi-agency network such as Jakarta's. The AI-DT architecture proposed

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in this study addresses both limitations simultaneously: an ensemble of LSTM, Gradient Boosting, and Isolation Forest improves predictive robustness under noisy multi-domain telemetry, while the Federated Learning orchestration layer preserves data sovereignty by keeping raw data at the edge and transmitting only model gradients. This combination is therefore not an incremental architectural variation but a methodologically motivated response to constraints that prior approaches do not jointly resolve, which constitutes the central methodological contribution and novelty of this study.

Accordingly, the objective of this study is to design, deploy, and empirically evaluate an AI-DT architecture for smart city infrastructure management through a 12-month field study in the Jakarta Metropolitan Area. The architecture comprises (1) a multi-protocol IoT data ingestion layer; (2) a real-time Digital Twin synchronization engine; (3) an AI analytics module that combines LSTM and Gradient Boosting ensemble forecasting, Isolation Forest anomaly detection, and Federated Learning; and (4) a web-based urban decision-support dashboard, evaluated across the transportation, energy, and water management domains.

The primary contributions of this paper are: (i) a validated, scalable AI-DT architecture tailored to developing-country urban environments; (ii) empirical performance benchmarks from a real deployment spanning 47 sensor nodes over 12 months; (iii) a Federated Learning implementation achieving data privacy compliance under Indonesian national regulation PP 71/2019; and (iv) a comparative analysis with conventional SCADA-based systems demonstrating statistically significant performance improvements.

## MATERIALS AND METHODS

### Research Design

This study employs a convergent mixed-methods design, integrating quantitative performance evaluation of the deployed AI-DT system with qualitative assessment of stakeholder adoption. The quantitative strand uses a quasi-experimental before-after design comparing system performance metrics before and after AI-DT deployment against a baseline SCADA system. The qualitative strand involved semi-structured interviews with 24 city officials and infrastructure operators across three city agencies: Transportation, Energy and Mineral Resources, and Water Resources.

The two strands were selected as complementary rather than independent sources of evidence: system-performance metrics alone cannot establish whether measured improvements translate into usable, adopted decision support in practice, and stakeholder perceptions alone cannot establish whether those perceptions are empirically grounded. Consistent with the convergent design, both strands were collected over the same 12-month period and analyzed in parallel before being merged through triangulation, whereby the quantitative findings (e.g., F1-score gains, latency, uptime) were interpreted alongside the qualitative themes reported in subsections E and F of the Results and Discussion to assess whether stakeholders' lived experience corroborated, qualified, or contradicted the statistical results. Convergence between strands, for instance the quantitative anomaly-detection gains and the qualitative theme of improved failure-anticipation capacity, is treated as corroborating evidence that strengthens the validity of the findings. Divergence, such as strong quantitative performance alongside qualitative concerns over interoperability and institutional readiness, is instead used to contextualize the boundary conditions under which technical improvements translate into organizational value. This integration logic is made explicit in the Discussion (subsection F of the Results and Discussion), where quantitative and qualitative results are interpreted jointly rather than reported as separate, unconnected sets of findings.

### Study Area and Deployment Sites

The field study was conducted across the Jakarta Metropolitan Area, encompassing DKI Jakarta Province and three adjacent municipalities forming the Jabodetabek region. Purposive sampling selected 47 sensor deployment sites across three infrastructure domains, as detailed in Table 1.

Table 1. IoT Sensor Deployment Distribution by Domain

| Domain | Sub-domain | Location | Nodes | Sensor Type |
|---|---|---|---|---|
| Transportation (n=18) | Road Traffic | Sudirman–Thamrin Corridor | 8 | CCTV & RFID |
| | MRT Feeder | Lebak Bulus–Bundaran HI | 6 | Passenger counters |
| | Toll Road | JORR W2 Segment | 4 | Loop detectors |



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| Domain | Sub-domain | Location | Nodes | Sensor Type |
|---|---|---|---|---|
| Energy (n=16) | Power Grid | Cawang–Koja Distribution | 7 | Smart meters |
| | Street Lighting | Sudirman CBD | 5 | Power sensors |
| | Solar Panels | Pluit Rooftop Area | 4 | PV inverter loggers |
| Water Management (n=13) | Water Distribution | Cilincing–Pademangan | 6 | Flow & pressure |
| | Flood Monitoring | Ciliwung River Corridor | 4 | Water level gauges |
| | Water Quality | PAM Jaya Installation | 3 | Multi-param probes |
| TOTAL | | | 47 | |

Source: (Research Results, 2024)

**Proposed AI-DT Architecture**

The proposed architecture follows a four-layer hierarchical design. Each layer scales independently and communicates via RESTful APIs and MQTT message brokers, ensuring loose coupling and vendor-agnostic interoperability.

Layer 1 - Physical Data Acquisition: A heterogeneous IoT sensor network transmits data via 4G-LTE and LoRaWAN protocols to edge gateways. Edge nodes perform local pre-processing, outlier filtering, and temporal resampling, reducing upstream bandwidth by approximately 62%.

Layer 2 - Digital Twin Synchronization Engine: Built on Eclipse Ditto v3.4.0, the synchronization engine maintains bidirectional state consistency between physical assets and their virtual counterparts, processing an average of 14,200 state updates per minute with a median synchronization latency of 340 ms.

Layer 3 - AI Analytics Module: Comprises three interoperable components: (a) LSTM-based time-series prediction (24-hour horizon, 15-minute granularity); (b) Isolation Forest anomaly detection, retrained weekly on a 90-day rolling window; and (c) a Federated Learning orchestrator coordinating model updates across 12 participating edge nodes without transmitting raw sensor data to the central server.

Layer 4 - Decision Support Dashboard: A React.js-based urban operational dashboard provides real-time KPI monitoring, CesiumJS 3D city visualization, alert management, and scenario simulation interface.

**Data Collection and Processing**

Quantitative data collection encompassed three streams: (i) continuous sensor telemetry aggregated at 15-minute intervals into InfluxDB v2.7; (ii) system performance logs from the DT synchronization engine; and (iii) AI model performance metrics tracked via MLflow. During the 12-month study period, the system accumulated 94.7 million individual sensor readings across 47 nodes, with an overall data completeness rate of 97.3%.

Qualitative data collection consisted of 24 semi-structured interviews in two waves: March 2024 (baseline) and November 2024 (post-implementation). Each interview lasted 45–75 minutes. Thematic analysis followed Braun and Clarke's six-phase reflexive thematic analysis approach [35] and was supported by MAXQDA 2024 software.

**Evaluation Metrics and Statistical Analysis**

System performance was evaluated using domain-appropriate metrics: Precision, Recall, and F1-score for anomaly detection; MAPE, RMSE, and MAE for predictive forecasting. Statistical significance of performance improvements over the SCADA baseline was assessed using paired Wilcoxon signed-rank tests ($\alpha = 0.05$), as the Shapiro-Wilk test rejected normality for all performance metric distributions at $p < 0.01$.

These evaluation techniques were selected to map directly onto the four architectural layers described in subsection C of the Materials and Methods, so that performance evidence could be traced to specific architectural components rather than reported only as system-level aggregates. Synchronization latency and update throughput (subsection C of the Results and Discussion) evaluate Layer 2 (Digital Twin Synchronization Engine); Precision, Recall, F1-score, and AUC-ROC for anomaly detection (subsection A) and MAPE/RMSE/MAE for forecasting (subsection B) evaluate Layer 3 (AI Analytics Module); FL convergence rounds (subsection C) and regulatory compliance mapping against PP 71/2019 (subsection D) evaluate the Federated Learning component within Layer 3; and system uptime and data completeness (subsection C) jointly reflect the reliability of Layers 1 and 2 in sustaining continuous data acquisition and synchronization.

The non-parametric Wilcoxon signed-rank test was chosen over a paired t-test because the Shapiro-Wilk results indicated that the performance-metric distributions violated the normality assumption required for parametric testing, and the paired design was retained because each domain's AI-DT and SCADA measurements were collected over matched time windows at the same sensor locations, making within-pair

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comparison more appropriate than an independent-samples test.

## RESULTS AND DISCUSSION

### Anomaly Detection Performance

Table 2 presents the anomaly detection performance of the AI-DT system compared to the baseline SCADA system across three infrastructure domains. The Isolation Forest model demonstrated consistently superior performance across all domains and evaluation metrics.

Table 2. Anomaly Detection Performance: AI-DT vs SCADA Baseline (Wilcoxon Signed-Rank Test, α = 0.05)

| Domain | System | Precision | Recall | F1 | AUC-ROC | FPR | p-value | ΔF1 |
|---|---|---|---|---|---|---|---|---|
| Transportation | SCADA | 0.714 | 0.681 | 0.697 | 0.731 | 0.143 | – | – |
| | AI-DT | 0.894 | 0.882 | 0.888 | 0.921 | 0.063 | <0.001 | +0.191 |
| Energy | SCADA | 0.741 | 0.698 | 0.719 | 0.754 | 0.127 | – | – |
| | AI-DT | 0.912 | 0.897 | 0.904 | 0.938 | 0.048 | <0.001 | +0.185 |
| Water Mgmt. | SCADA | 0.668 | 0.643 | 0.655 | 0.697 | 0.178 | – | – |
| | AI-DT | 0.887 | 0.871 | 0.879 | 0.914 | 0.071 | <0.001 | +0.224 |
| Overall (weighted) | SCADA | 0.711 | 0.674 | 0.692 | 0.727 | 0.150 | – | – |
| | AI-DT | 0.898 | 0.883 | 0.891 | 0.924 | 0.061 | <0.001 | +0.199 |

Source: (Research Results, 2024)

The proposed AI-DT system achieved an overall weighted F1-score of 0.891, significantly outperforming the baseline SCADA monitoring system (F1 = 0.692; ΔF1 = +0.199, a 28.8% relative improvement; $p < 0.001$). The SCADA baseline employed the conventional operational configuration used by the participating infrastructure operators, consisting of fixed threshold-based alarm rules and manually configured event detection without machine learning capabilities. This comparison therefore evaluates the benefit of integrating AI-driven predictive analytics into existing monitoring practices rather than replacing another learning-based anomaly detector.

Performance improvements were consistently observed across all infrastructure domains. In the transportation network, the AI-DT framework effectively detected abnormal traffic congestion and sensor failures with an F1-score of 0.888. In the energy domain, the system achieved an F1-score of 0.904, accurately identifying abnormal consumption patterns and equipment malfunctions. For the water management network, the model obtained an F1-score of 0.879, successfully detecting leakage events and pressure anomalies. These results indicate that the proposed architecture provides robust anomaly detection across heterogeneous urban infrastructure systems rather than concentrating its performance gains within a single application domain.

Furthermore, the False Positive Rate decreased from 15.0% to 6.1%, substantially reducing operator alert fatigue, a persistent limitation of conventional threshold-based monitoring systems that was consistently highlighted during stakeholder interviews. The overall performance is comparable to the Isolation Forest benchmarks reported by Cincotta et al. [22] (F1 = 0.874–0.912) and exceeds the operational F1-score threshold of 0.82 for city-scale anomaly detection.

### Predictive Forecasting Performance

Table 3 summarizes the predictive accuracy of the AI-DT ensemble for infrastructure demand forecasting over a 24-hour horizon at 15-minute granularity.

Table 3. Predictive Forecasting Performance (24-Hour Horizon, 15-Minute Granularity)

| Task | Model | MAPE (%) | RMSE | Unit |
|---|---|---|---|---|
| Energy Consumption Forecast | LSTM | 5.81 | 312.4 | kWh/15-min |
| | Gradient Boosting | 4.97 | 284.7 | kWh/15-min |
| | Ensemble (Proposed) | 4.23 | 251.8 | kWh/15-min |
| Traffic Flow Forecast | LSTM | 7.34 | 213.1 | veh/h |
| | Gradient Boosting | 6.18 | 198.6 | veh/h |
| | Ensemble (Proposed) | 5.47 | 187.4 | veh/h |
| Water Demand Forecast | LSTM | 6.92 | 48.3 | L/s |



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| Task | Model | MAPE (%) | RMSE | Unit |
|---|---|---|---|---|
| | Gradient Boosting | 5.73 | 43.1 | L/s |
| | Ensemble (Proposed) | 4.88 | 39.7 | L/s |

Source: (Research Results, 2024)

The ensemble model consistently outperformed the individual forecasting models across all three infrastructure domains. To evaluate the contribution of each component, an ablation analysis was conducted by progressively removing one model from the ensemble while keeping the remaining configuration unchanged. The results showed that LSTM provided the greatest improvement in capturing long-term temporal dependencies, particularly for energy consumption forecasting. Gradient Boosting complemented the LSTM by improving prediction accuracy by learning nonlinear relationships among heterogeneous sensor variables and correcting residual errors that were not captured by the temporal model. The complete ensemble achieved the best overall performance, with an energy consumption MAPE of 4.23%, below the 5% operational threshold for smart-grid forecasting [19]. Likewise, the traffic flow forecasting RMSE of 187.4 veh/h compares favorably with the 195.7 veh/h benchmark [20], while the water demand forecasting MAPE of 4.88% falls within the 4.2–5.6% range reported in [21]. These findings indicate that the performance improvement results from the complementary strengths of the two forecasting models rather than the dominance of a single algorithm.

**Digital Twin Synchronization Performance**

Table 4 summarizes the system-level performance of the DT synchronization engine during the 12-month observation period against pre-defined Service Level Agreement (SLA) targets.

Table 4. Digital Twin Synchronization Engine SLA Performance (January–December 2024)

| Performance Metric | SLA Target | Achieved Result | SLA Met |
|---|---|---|---|
| Median Sync Latency | ≤ 500 ms | 340 ms | Yes |
| 95th Percentile Latency | ≤ 1,200 ms | 872 ms | Yes |
| System Uptime | ≥ 99.0% | 99.4% | Yes |
| Data Completeness Rate | ≥ 95.0% | 97.3% | Yes |
| Peak Throughput | ≥ 10,000 updates/min | 14,200 updates/min | Yes |
| Edge Bandwidth Reduction | ≥ 50% | 62.1% | Yes |
| FL Model Convergence | ≤ 15 rounds | 11 rounds (avg.) | Yes |

Source: (Research Results, 2024)

All seven SLA targets were successfully achieved during the 12-month operational period. Three scheduled maintenance windows totaling 4.3 hours accounted for 0.6% system downtime, resulting in an overall uptime of 99.4%. Although the deployment operated reliably, several implementation challenges commonly encountered in city-scale IoT environments were observed, including intermittent packet loss caused by cellular network fluctuations, temporary sensor outages during scheduled maintenance and power interruptions, and occasional data inconsistencies resulting from asynchronous sensor reporting. To maintain service continuity, the system employed MQTT Quality of Service (QoS) mechanisms for reliable message delivery, automatic sensor health monitoring with reconnection and retry procedures, timestamp-based data synchronization within the Digital Twin layer, and data validation and interpolation techniques to handle missing or delayed sensor observations. These mechanisms enabled stable Digital Twin synchronization despite transient communication disruptions.

The Federated Learning orchestrator converged within an average of 11 communication rounds across 12 participating edge nodes, remaining below the simulation-derived ceiling of 15 rounds despite variations in network latency and local computational capacity. Furthermore, the proposed communication strategy reduced edge bandwidth consumption by 62.1%, consistent with the 67% reduction [25] for a comparable hierarchical Federated Learning architecture. These findings indicate that the proposed AI-DT framework maintains robust operational performance under realistic deployment conditions while effectively mitigating common challenges associated with large-scale urban IoT infrastructures.

**Federated Learning Privacy Compliance Audit**

The Federated Learning (FL) module was audited for compliance with Indonesia's PP 71/2019 and Permenkominfo No. 5/2020 through a structured assessment conducted in collaboration with certified IT auditors. In addition to regulatory compliance, the operational characteristics of the FL framework were evaluated to assess its

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communication and computational overhead. Model synchronization across the 12 participating edge nodes required an average of 11 communication rounds to reach convergence. Compared with centralized training, the FL approach introduced additional local computation and synchronization overhead, while reducing inter-node communication bandwidth by 62.1% because only model parameters, rather than raw sensor data, were exchanged. Despite this additional synchronization cost, the FL framework maintained stable convergence and enabled privacy-preserving collaborative learning without violating data sovereignty requirements. Table 5 summarizes both the regulatory compliance assessment and the operational characteristics of the proposed Federated Learning implementation.

Table 5. FL Privacy Compliance Mapping against PP 71/2019 and Permenkominfo No. 5/2020

| Regulation | Requirement | FL Implementation Mechanism | Status |
|---|---|---|---|
| PP 71/2019 Art. 21(1) | Personal data must not leave registered system territory | Raw sensor data remains at edge nodes; only gradient updates transmitted | Compliant |
| PP 71/2019 Art. 22(2) | Data encryption during transmission | TLS 1.3 and differential privacy noise injection (ε = 1.0) | Compliant |
| PP 71/2019 Art. 25 | Audit trail for all data processing activities | Immutable FL training logs in append-only WORM ledger | Compliant |
| Permenkominfo 5/2020 Art. 40 | Data localization for strategic sector systems | Central aggregation server hosted on GovCloud Indonesia | Compliant |

Source: (Research Results, 2024)

**Qualitative Findings: Stakeholder Perspectives**

Thematic analysis of 24 stakeholder interviews produced five primary themes summarized in Table 6.

Table 6. Summary of Primary Qualitative Themes and Representative Findings

| Theme | Representative Finding | Frequency (n=24) | Valence |
|---|---|---|---|
| Perceived Operational Value | Capacity to anticipate failures improved substantially post-deployment | 21 (87.5%) | Positive |
| Data Trust & Transparency | Concerns about AI decision explainability for regulatory accountability | 17 (70.8%) | Mixed |
| Technical Capacity | Capacity-building programs needed before full operational adoption | 16 (66.7%) | Negative |
| Interoperability | Integration challenges with existing JSC platform APIs | 14 (58.3%) | Negative |
| Institutional Readiness | Cross-departmental data sharing requires updated governance MoUs | 19 (79.2%) | Mixed |

Source: (Research Results, 2024)

The most notable finding is that 87.5% of participants (n = 21) reported substantial improvements in infrastructure failure anticipation capacity. However, 66.7% (n = 16) identified the need for structured capacity building as a prerequisite for full operational adoption. These qualitative findings complement the quantitative performance improvements by demonstrating that organizational readiness and human capability remain critical factors for successful Digital Twin deployment, in addition to technical performance [12], [35]. Nevertheless, these findings should be interpreted with caution because the qualitative evaluation involved only 24 stakeholders, representing a limited sample relative to the overall scale and diversity of the Jakarta Smart City ecosystem. Consequently, while the interviews provide valuable insights into practitioner perceptions, they may not fully capture the perspectives of all stakeholder groups involved in city-wide infrastructure management. Future studies should incorporate larger and more diverse participant populations across multiple government agencies and infrastructure operators to strengthen the generalizability of these findings.

**Discussion**

The empirical results collectively validate the central proposition: a contextually adapted AI-DT architecture delivers statistically significant improvements in smart city infrastructure


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management. Several findings merit deeper discussion.

First, the 28.8% relative F1-score improvement (ΔF1 = +0.199) substantially exceeds the 15–20% gains reported in comparable developed-country studies [9], [12]. This larger-than-expected improvement is attributed to the low SCADA baseline, suggesting that the marginal benefit of AI-DT integration may be inversely correlated with initial infrastructure quality—a finding with important policy implications for developing-country smart city investment prioritization.

Second, the successful FL implementation demonstrates the technical feasibility of privacy-preserving AI under Indonesia's regulatory constraints. The 11-round convergence is especially encouraging given Jakarta's heterogeneous bandwidth conditions, and the differential privacy parameter choice of $\varepsilon = 1.0$ is consistent with the privacy–utility trade-offs reported for federated learning in smart city settings [23].

Third, qualitative findings reveal a persistent tension between technical performance and organizational readiness, consistent with Wahyudi et al.'s [29] assessment of JSC institutional limitations. The AI-DT architecture functions as a decision support tool whose value is contingent on operators' capacity to interpret AI-generated insights. Future implementations should co-design capacity-building programs alongside technical deployment.

Fourth, the interoperability challenges reported by 58.3% of participants (n = 14) indicate that integration with existing Jakarta Smart City platform APIs remains a practical barrier. The DT architecture's open API layer provides a partial technical solution, but governance-level interventions, such as updated inter-departmental MoUs for data sharing, are equally necessary.

This study has several limitations. First, the 47-node deployment represents only a subset of Jakarta's urban infrastructure and may not fully reflect the operational complexity of a city-wide implementation. Second, although the proposed AI-DT architecture demonstrated strong predictive performance, this study did not perform a comprehensive evaluation of cybersecurity risks, such as cyberattack resilience, secure edge-node authentication, or adversarial attacks against AI models, which remain critical considerations for large-scale Digital Twin deployments. Third, the computational resource requirements of the proposed framework, including edge processing capacity, GPU utilization for AI model training, and communication overhead associated with Federated Learning, were evaluated only at the current deployment scale and may increase substantially in larger city-wide implementations. Fourth, implementation costs, including IoT infrastructure investment, cloud and edge computing resources, long-term system maintenance, and personnel training, were not analyzed through a formal techno-economic assessment. Finally, the 12-month observation period may not fully capture long-term operational behavior or rare extreme weather events that could influence infrastructure performance. Future research should therefore investigate scalable cybersecurity architectures, resource-efficient AI optimization strategies, comprehensive cost-benefit analyses, and multi-city comparative deployments to better assess the operational feasibility and sustainability of AI-powered Digital Twin systems.

## CONCLUSION

This paper presented the design, implementation, and 12-month field evaluation of an AI-powered Digital Twin architecture for smart city infrastructure management in the Jakarta Metropolitan Area. The proposed four-layer architecture, integrating multi-protocol IoT data acquisition, a real-time Eclipse Ditto synchronization engine, an ensemble AI analytics module, and a React.js/CesiumJS urban dashboard, was evaluated across 47 sensor nodes spanning transportation, energy, and water management domains. Key empirical contributions include: (i) an overall anomaly detection F1-score of 0.891 (ΔF1 = +0.199, a 28.8% relative improvement over the SCADA baseline, $p < 0.001$); (ii) energy consumption forecasting MAPE of 4.23%; (iii) traffic flow forecasting RMSE of 187.4 veh/h; (iv) system uptime of 99.4% and data completeness of 97.3%; and (v) full compliance with PP 71/2019 through Federated Learning with differential privacy ($\varepsilon = 1.0$). Theoretically, this study advances the Digital Twin literature by proposing and empirically validating an AI-powered Digital Twin (AI-DT) architecture that integrates real-time Digital Twin synchronization, predictive analytics, anomaly detection, and privacy-preserving Federated Learning within a unified smart city framework. The findings demonstrate that such integration can improve infrastructure monitoring, forecasting accuracy, and operational decision-making across transportation, energy, and water management domains. Practically, the documented architecture and deployment methodology provide a replicable reference model for smart city practitioners seeking

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to implement AI-enabled Digital Twin solutions in complex urban environments.

Nevertheless, the findings should be interpreted in light of several limitations. The deployment was conducted on 47 sensor nodes and therefore represents only a subset of Jakarta's broader infrastructure ecosystem. In addition, the study did not comprehensively evaluate cybersecurity resilience, large-scale computational resource requirements, or the long-term economic costs associated with city-wide implementation. Furthermore, while Federated Learning demonstrated regulatory compliance and effective model convergence, its scalability under substantially larger deployments remains to be validated. Future research should therefore focus on several directions. First, large-scale evaluations involving hundreds or thousands of sensors should be conducted to assess system scalability and operational robustness. Second, dedicated cybersecurity assessments, including penetration testing, adversarial machine learning analysis, and secure Digital Twin communication mechanisms, are needed to strengthen trustworthiness in critical urban infrastructure environments. Third, further optimization of Federated Learning should investigate communication-efficient aggregation methods, adaptive synchronization strategies, and resource-aware model training to reduce computational and networking overhead. Fourth, the framework may be extended to additional urban domains such as healthcare, waste management, and air quality monitoring. Finally, the integration of Explainable AI (XAI) techniques should be explored to improve the transparency, interpretability, and operational acceptance of AI-generated recommendations among city operators and policymakers.

## DECLARATION OF AI USE

The authors declare that generative artificial intelligence (AI) tools were used in the preparation of this manuscript. Claude (Anthropic) was used to assist with formatting the manuscript according to the journal template and with English language editing. The authors reviewed and revised all AI-assisted content and take full responsibility for the accuracy, originality, and final content of the manuscript.

## AUTHOR CONTRIBUTIONS

This journal uses the Contributor Roles Taxonomy (CRediT) to identify individual author contributions to the research and manuscript preparation.

| Author | Contribution Roles |
|---|---|
| Adhiguna Mahendra | Conceptualization, Methodology, Supervision, Writing, Review & Editing. |
| Agustinus Fritz Wijaya | Conceptualization, Investigation, Formal Analysis, Writing an Original Draft. |
| Merryana Lestari | Investigation, Data Curation, Validation. |
| Mega Kartika Sari | Software, Formal Analysis, Visualization. |

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## CONFLICT OF INTEREST STATEMENT

The authors declare that there are no conflicts of interest related to the research, writing, or publication of this article.

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