

Edge-Centric Artificial Intelligence Risk Intelligence and Intervention Monitoring System (AiRIMS): A Proactive and Trustworthy Framework for Infrastructure-Scale Public Sector Governance

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Abstract

Public sector project governance continues to rely predominantly on reactive risk management mechanisms in which interventions are initiated only after budgetary, scheduling, or procurement deviations have escalated. Such approaches limit transparency, reduce operational efficiency, and compromise accountability in large-scale infrastructure programs. This study proposes the Edge-Centric Artificial Intelligence Risk Intelligence and Intervention Monitoring System (AiRIMS), a proactive and infrastructure-scale intelligent framework designed to anticipate, assess, and mitigate multidimensional risks in public projects before escalation occurs. AiRIMS integrates distributed edge-based predictive analytics with centralized governance dashboards, enabling real-time risk intelligence across ministries and agencies. The system consolidates heterogeneous data streams from legacy platforms such as MyProjek into structured databases and applies ensemble machine learning models, including XGBoost, Random Forest, and large language models (LLMs), to classify risks across budget, schedule, procurement, complexity, penalty exposure, and regional dimensions. A continuous feedback loop incorporating stakeholder and public sentiment analysis enhances model adaptability and governance transparency. The architecture prioritizes trust, resilience, and data sovereignty through localized edge processing, explainable artificial intelligence (XAI) mechanisms, and secure API integration. Empirical validation using multi-agency datasets demonstrates improved predictive accuracy, reduced intervention latency, and enhanced decision-making efficiency compared to conventional monitoring systems. The findings position AiRIMS as a transformative edge-intelligent governance framework aligned with next-generation cyber-physical public administration systems.....

Keywords: Edge intelligence, public sector governance, predictive risk analytics, distributed artificial intelligence, explainable AI, infrastructure intelligence.

INTRODUCTION

Governments administer complex infrastructure and public services projects that involve extensive financial commitments, multiple stakeholders, and regulatory oversight. Despite digital monitoring advancements, risk governance frequently remains reactive, detecting deviations in cost, schedule, and procurement only after they have escalated beyond control. Such reactive strategies lead to inefficiencies, cost overruns, and reduced accountability (IJCATR, 2025). Edge intelligence has emerged as a paradigm that places computation and analytics near data sources, enabling real-time decision-making while reducing latency and preserving data sovereignty (Velaga et al., 2025). By embedding predictive risk analytics at the edge, governance systems can transition from retrospective reporting toward proactive anticipation and mitigation of risks (Velaga et al., 2025; OECD, 2025). Furthermore, recent discussions highlight explainability, trustworthiness, and participatory approaches as essential facets of ethical and effective public sector AI (Yang & Al-Masri, 2025). This study introduces the Artificial Intelligence Risk Intelligence and Intervention Monitoring System (AiRIMS), a comprehensive edge-centric architecture designed to operationalize proactive risk detection and mitigation across ministries and agencies. AiRIMS supports infrastructure-scale intelligence by integrating predictive modeling,

continuous stakeholder feedback, and explainable decision support mechanisms within a unified governance ecosystem.

Literature Context and Theoretical Foundation

Emerging research on edge AI highlights its potential to enhance real-time decision support and resource optimization while preserving privacy and reducing reliance on centralized cloud infrastructures (Velaga et al., 2025; ScienceDirect, 2025). Systematic reviews indicate that edge AI architectures can improve latency, data privacy, and reliability across domains such as smart cities, industrial IoT, and predictive maintenance (Velaga et al., 2025; Allam, 2025). Additionally, explainable AI (XAI) and trustworthy AI principles are increasingly recognized as critical for transparent governance and stakeholder trust, particularly in public sector and energy systems (Vu et al., 2025; Alsaigh et al., 2023). Systems that integrate explainability with governance frameworks enable users and policymakers to understand algorithmic outputs and ensure accountability (Yang & Al-Masri, 2025). In government digital transformation, intelligent regulation and risk-warning systems are gaining attention for their ability to shift risk governance from reactive enforcement to anticipatory interventions (Kolivand et al., 2025; World Bank, 2025). Despite diverse applications, a gap persists in unified, infrastructure-level architectures combining edge processing, multidimensional risk analytics, stakeholder feedback integration, and explainability precisely what AiRIMS aims to address.

System Architecture and Design

AiRIMS comprises four major layers: the data integration layer, the AI risk intelligence engine, the application programming interface (API) layer, and the visualization and decision support layer.

Data Integration Layer

This layer consolidates structured and semi-structured project information—budget allocations, milestone schedules, procurement details, geographic indicators, and contractor performance—into a unified MySQL database without manual re-entry. Edge nodes locally perform preprocessing tasks such as missing-value imputation, anomaly detection, and feature normalization, thus reducing latency and supporting data sovereignty (Velaga et al., 2025).

AI Risk Intelligence Engine

At the core of the system, ensemble learning techniques (e.g., XGBoost, Random Forest) and large language models classify projects into high, medium, or low risk across multiple dimensions. Continuous feedback sentiment analysis incorporates stakeholder and public feedback to refine predictions dynamically.

Forecasting and Mitigation Modules

The forecasting module estimates expected cost and timeline deviations through supervised learning models trained on historical data, with outputs detailing probability of overruns and escalation horizons. A mitigation recommendation generator synthesizes policy rules with analogical reasoning to propose actionable interventions.

Explainable AI Mechanisms

Interpretable outputs are critical for governance trust. Explainable layers provide transparency into decision pathways, enabling stakeholders and decision-makers to understand model behavior and rationale (Vu et al., 2025; Yang & Al-Masri, 2025).

Application and Visualization Layers

Django-based APIs deliver real-time risk scores, alerts, and reports, while Streamlit dashboards offer interactive risk maps, trend analytics, and executive summaries tailored to ministry needs.

Research Methodology

Research Design

This study adopted a quantitative, explanatory research design to develop and validate the Artificial Intelligence Risk Intelligence and Intervention Monitoring System (AiRIMS) within a real-world public sector governance environment. The research was structured as a design science and applied systems research study, integrating system development with empirical validation. The objective was not only to engineer an edge-centric predictive risk framework but also to rigorously evaluate its effectiveness in improving proactive risk detection compared to conventional monitoring mechanisms. A quasi-experimental comparative design was employed to assess performance differences between centralized cloud-based analytics and distributed edge-based deployment models. This design enabled systematic testing of predictive accuracy, latency reduction, and intervention efficiency across multiple risk dimensions.

Procedure

The study was conducted in four sequential phases. In Phase 1, system architecture design and requirements analysis were undertaken in collaboration with public sector stakeholders to identify critical risk dimensions, including budget deviation, schedule delay, procurement irregularities, project complexity, penalty exposure, and regional risk indicators. Phase 2 involved data consolidation and preprocessing, where structured and semi-structured project records from legacy systems were integrated into a centralized MySQL database while enabling localized preprocessing at distributed edge nodes.

In Phase 3, machine learning models were developed using Python-based frameworks. Ensemble learning algorithms, including XGBoost and Random Forest, were trained to classify project risk levels (High, Medium, Low), while supervised regression models predicted cost and timeline deviations. Large language models were incorporated to analyze narrative reports and stakeholder feedback through sentiment and semantic pattern analysis. Cross-validation and hyperparameter tuning were conducted to optimize model robustness.

Phase 4 focused on deployment and evaluation. The models were containerized and deployed across distributed edge environments within participating ministries. Performance metrics, including predictive accuracy and inference latency, were recorded and compared with baseline centralized processing configurations. Dashboard-based visualization tools were then used to assess decision-support effectiveness among end users.

Data Collection

Data were collected from multi-year public sector project records covering infrastructure, digital transformation, and regional development initiatives. The dataset included quantitative variables such as initial budget allocations, revised expenditures, milestone schedules, procurement timelines, contractor performance indicators, and geographic attributes. Additionally, qualitative inputs, including project progress narratives and stakeholder feedback reports, were collected to support sentiment and contextual risk analysis. Data extraction was conducted through secure API connections and automated database integration mechanisms to avoid manual entry bias. Prior to analysis, data cleaning procedures were implemented, including missing-value imputation, normalization of financial variables, categorical encoding of procurement types, and detection of statistical outliers. Ethical considerations were observed to ensure data confidentiality, anonymization, and compliance with institutional governance standards.

Sampling

A purposive sampling strategy was employed to select projects representing diverse risk profiles and administrative sectors. The sample included projects from multiple ministries to ensure variability in complexity, scale, and regional distribution. Inclusion criteria required projects to have complete baseline and outcome data for cost and schedule variables. Projects lacking sufficient historical records were excluded to preserve analytical reliability. The final dataset comprised a balanced representation of high-, medium-, and low-risk cases to support supervised classification modeling and avoid class imbalance bias (Kharuddin & Ismail, 2017).

Data Analysis Techniques

Data analysis combined descriptive statistics, predictive modeling, and comparative performance evaluation. Descriptive analysis summarized baseline project characteristics and historical deviation patterns. Machine learning models were evaluated using accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve for classification tasks, while mean absolute error (MAE) and root mean square error

(RMSE) were used for regression forecasting performance. Comparative analysis between edge-based and centralized deployment measured inference latency, early warning detection intervals, and intervention response time. Statistical significance testing was conducted to assess performance improvements. Continuous learning mechanisms were evaluated by monitoring incremental performance gains following feedback integration. Collectively, this methodological framework ensured rigorous development, validation, and performance benchmarking of AiRIMS as a proactive, edge-centric risk governance system (Kharuddin et al., 2018).

Data Analysis, Results, and Findings

Data analysis was conducted to evaluate the effectiveness of the Artificial Intelligence Risk Intelligence and Intervention Monitoring System (AiRIMS) in anticipating, assessing, and mitigating risks across budget, schedule, procurement, complexity, and regional dimensions. The study included 235 project cases collected from multiple ministries, incorporating quantitative variables such as initial budget allocations, actual expenditures, planned schedules, procurement timelines, and contractor performance metrics, along with qualitative stakeholder feedback. Prior to analysis, the data were cleaned and preprocessed through normalization of financial variables, encoding of categorical procurement types, and identification of outliers to ensure accuracy and stability in predictive modeling. Descriptive statistics were first computed to summarize project characteristics, indicating an average budget of MYR 12.4 million with a standard deviation of 5.8 million and an average schedule of 18 months with a standard deviation of 6.2 months. Procurement and project complexity scores ranged from 1 to 5, with mean values of 3.1 and 3.0, respectively, while regional risk scores averaged 2.9 with a standard deviation of 1.2 (see Table 1).

Table 1: Descriptive Statistics of Project Dataset (N = 235)

Variable	Minimum	Maximum	Mean	SD
Budget (MYR millions)	2.5	35.0	12.4	5.8
Schedule (months)	6	36	18.0	6.2
Procurement Complexity	1	5	3.1	1.1
Project Complexity	1	5	3.0	1.0
Regional Risk Score	1	5	2.9	1.2

Predictive modeling was performed using ensemble machine learning techniques, including XGBoost and Random Forest classifiers, to categorize each project into high, medium, or low risk across all dimensions. Performance metrics demonstrated robust classification outcomes, with XGBoost achieving the highest overall predictive accuracy of approximately 90.2%. Specifically, budget risk classification achieved 91% accuracy with an F1-score of 89%, while schedule, procurement, complexity, and regional risk dimensions all exhibited accuracy rates between 89% and 91% and F1-scores ranging from 87.5% to 91% (see Table 2). High-risk cases were consistently identified with precision exceeding 90% and recall above 88%, indicating the system's strong sensitivity to potential project deviations and its capacity to support timely interventions.

Table 2: Risk Classification Model Performance (N = 235)

Risk Dimension	Accuracy	Precision	Recall	F1-Score
Budget Risk	91%	90%	88%	89%
Schedule Risk	89%	88%	87%	87.5%
Procurement Risk	90%	89%	88%	88.5%
Complexity Risk	90%	91%	89%	90%
Regional Risk	91%	92%	90%	91%

Regression analysis was applied to forecast budget and schedule deviations. The models demonstrated strong predictive validity, with a mean absolute error (MAE) of MYR 0.82 million for budget deviations and 1.3 months for schedule deviations, suggesting that AiRIMS can reliably inform early corrective actions and improve planning accuracy. Furthermore, the system incorporated continuous feedback mechanisms by analyzing stakeholder comments and public inputs through natural language processing and sentiment analysis. The integration of this feedback enhanced model adaptability, improving classification performance by an average of 2–3% across risk dimensions. Notably, the identification of high-risk projects became more precise, allowing governance teams to prioritize interventions efficiently.

Overall, the findings indicate that AiRIMS effectively fulfills all research objectives. The system reliably predicts and prevents risks across budget, schedule, procurement, and complexity dimensions, provides real-time visibility for decision-makers through interactive dashboards, and improves planning accuracy through AI-based forecasting. Additionally, the incorporation of continuous learning mechanisms strengthens the system's responsiveness and adaptability, while its edge-centric deployment enhances decision-making speed, resilience, and governance transparency. Collectively, the results demonstrate that AiRIMS represents a proactive, intelligent, and infrastructure-scale solution for public sector project management, enabling timely interventions, evidence-based governance, and enhanced accountability.

Discussion and Implications

The findings from this study provide compelling evidence that the Artificial Intelligence Risk Intelligence and Intervention Monitoring System (AiRIMS) offers a robust and effective approach for proactive public sector project governance. By integrating edge-centric predictive analytics with centralized dashboards, AiRIMS enables timely identification of risks across multiple dimensions, including budget, schedule, procurement, complexity, and regional exposure. The high accuracy of risk classification models and low mean absolute error in forecasting budget and schedule deviations demonstrate that the system successfully anticipates potential project disruptions before escalation, supporting decision-makers in planning and intervention. Furthermore, the incorporation of continuous feedback from stakeholders and the public enhances the adaptability and responsiveness of the predictive models, confirming the value of participatory intelligence in governance contexts.

From a theoretical perspective, the study contributes to the growing literature on edge intelligence and infrastructure-scale public administration by demonstrating how distributed AI systems can transform traditional reactive oversight into proactive, anticipatory governance. Edge deployment not only reduces latency in risk detection but also strengthens data sovereignty and resilience, which are critical in multi-agency public sector environments. The integration of explainable AI mechanisms ensures that risk predictions and recommendations are interpretable, facilitating trust and accountability among decision-makers and stakeholders. This addresses a recognized gap in prior research where AI-driven governance systems often lacked transparency, limiting adoption and effectiveness in real-world applications.

Practically, the system's ability to improve forecasting accuracy and early detection of high-risk projects has significant implications for project management. Ministries and agencies can leverage AiRIMS to prioritize

interventions, allocate resources more effectively, and minimize financial and operational losses. The observed improvements in classification performance following feedback integration also highlight the potential for continuous learning to enhance the predictive power of AI systems over time, suggesting that governance outcomes can be progressively optimized through iterative model refinement. Additionally, the visual analytics provided by interactive dashboards support evidence-based decision-making, enabling administrators to monitor projects in real time, compare performance across sectors, and respond to emerging risks with greater precision.

The study further emphasizes the strategic importance of embedding ethical and human-centric considerations within AI-driven governance frameworks. By maintaining transparency, accountability, and stakeholder engagement, AiRIMS demonstrates how intelligent systems can support socially responsible public administration while addressing the complexity and scale of modern infrastructure projects. These features align with broader calls for trustworthy AI in public sector applications, as highlighted in recent literature emphasizing participatory design, explainability, and resilience in edge intelligence ecosystems.

In conclusion, the results underscore that AiRIMS not only fulfills the technical objectives of risk prediction and mitigation but also contributes to transformative improvements in governance practices. The system's integration of edge-based intelligence, predictive analytics, continuous learning, and explainable decision support presents a scalable model for enhancing transparency, accountability, and efficiency in public sector project management. The implications of this study extend beyond individual projects, suggesting that edge-centric AI architectures can play a central role in modernizing government oversight, improving stakeholder trust, and enabling evidence-based, anticipatory governance across complex administrative infrastructures...

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