Jurnal Kecerdasan Buatan dan Teknologi Informasi
Vol. 5, No. 2, May 2026, pp. 137-142
e-ISSN: 2964-2922, p-ISSN: 2963-6191
DOI : https://doi.org/10.69916/jkbti.v5i2.445

DESIGN AND DEVELOPMENT OF AN EARLY WARNING SYSTEM THROUGH CONTINUOUS AUDITING AND CONTINUOUS MONITORING IN PUBLIC SECTOR PROCUREMENT

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(Received: April 18, 2026; Revised: April 24, 2026; Published: May 2, 2026)

Abstract

The background of this research is the challenge in supervising goods and services procurement in the public sector, which is still dominated by traditional, reactive auditing methods conducted after transactions are finalized. The primary issue is the high volume of transactions and data complexity, which hinders early fraud detection. This research aims to design and develop an early warning system using Continuous Auditing and Continuous Monitoring (CACM) methods to enhance the effectiveness of fraud detection. The research method involves system development based on data integration from the Electronic Procurement System (SPSE) and other supporting monitoring systems. By utilizing data analytics, the system is designed to automatically identify risk indicators based on tender winner patterns and bidding behavior. The results indicate that CACM implementation enables real-time anomaly identification, providing early warning signals for auditors to take preventive measures before broader irregularities occur. In conclusion, the application of the CACM system transforms the internal oversight paradigm into a more proactive approach, strengthening fraud detection capabilities while improving accountability and transparency in government procurement processes.

Keywords: continuous auditing; continuous monitoring; public procurement; early warning system; fraud detection.

1. INTRODUCTION

Public Procurement of Goods and Services (PBJ) serves as a vital sector in public institution operations, involving significant budget allocations. However, the complexity of business processes and the high volume of transactions create potential vulnerabilities for fraudulent practices. Historical data obtained from a central government ministry in Indonesia between 2016 and 2020 indicates a highly concentrated distribution of tender winners among certain partner entities, both in terms of the number of packages and contract values won. This pattern emphasizes the necessity for more stringent oversight to ensure fair competition and prevent collusion[1]. Traditional oversight methods, which rely on post-audit approaches, are currently perceived as less effective. Manual auditing is time-consuming and often only identifies irregularities after the transactions have been completed. Conversely, the trend of digital transformation demands an oversight system capable of operating in sync with data velocity[2]. In the Industry 4.0 era, leveraging information technology for continuous monitoring has become an urgent requirement for government internal audit units [3].

Previous studies have discussed the effectiveness of technology-based auditing. However, a review of the existing literature reveals that most studies have not yet integrated diverse data sources, such as procurement plans, electronic tendering systems (SPSE), and real-time contract execution monitoring, effectively. Consequently, most existing systems operate partially and have not yet provided a comprehensively integrated early warning signal [4]. This research aims to bridge this gap by designing a Continuous Auditing and Continuous Monitoring (CACM) system. The novelty of this research lies in the development of a unified CACM framework that synthesizes multiple critical fraud indicators, specifically tender winner concentration, partner capacity threshold violations, and document metadata similarities, into a single, real-time cloud-based monitoring dashboard specifically tailored for the Indonesian public procurement context. Unlike prior systems that often operate in silos or rely on post-audit retrospective analysis, this approach provides a proactive, integrated early warning system designed to identify procedural irregularities at multiple stages of the procurement lifecycle, thereby enabling immediate corrective measures before contract finalization. The system is designed to automate data extraction and present it through a visual dashboard capable of providing early warnings for procurement behavior anomalies. Through the implementation of CACM, it is expected that the oversight process will evolve from a purely administrative function into a strategic decision-making tool to enhance public sector accountability.[5]

2. RESEARCH METHODS

This research adopted an Agile/Scrum methodology for the development of the CACM system[6]. The choice of the Agile/Scrum framework is justified by the complexity of the data integration process and the need for iterative refinements based on stakeholder feedback [7].

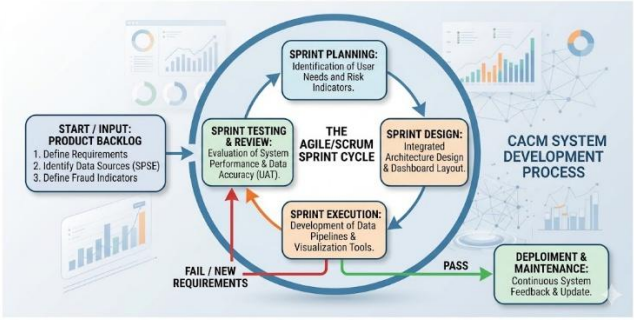

Figure 1. Agile/Scrum Framework applied to the CACM System

Figure 1. CACM System Architecture and Data Integration Workflow. This diagram illustrates the data flow from source systems through the ETL process to the visualization dashboard. The cycle operates through the following phases [8]:

1. Sprint Planning: This initial phase focuses on defining system requirements, identifying necessary data sources (e.g., SPSE), and establishing specific fraud indicators.
2. Sprint Design: This phase involves the development of the system's architectural framework and the design of the real-time monitoring dashboard interface.
3. Sprint Execution: The technical phase where data pipelines are constructed, and analytical algorithms are implemented into the system.
4. Sprint Testing & Review: The system is evaluated against predefined performance criteria and data accuracy standards to ensure functional integrity.

2.1. Data Identification and Acquisition

The initial phase involved identifying primary data sources relevant to the procurement process. The datasets included procurement general plans, electronic tender processing data from the SPSE, and physical and financial realization reports. In this context, researchers abstracted historical datasets of tender winners to identify key risk variables, such as winner concentration and the frequency of participation by specific partners.[9]

2.2. CACM System Architecture Design

The architecture of the CACM system is designed to automate the integration of procurement data, ensuring a seamless flow from raw data sources to actionable insights. Figure 1 illustrates the data integration workflow, detailing the path from operational data sources (SIRUP, SPSE, and e-Mon) through an Extraction, Transformation, and Loading (ETL) process [10]. The data integration process relies on an automated ETL (Extract, Transform, Load) pipeline scheduled for daily execution. This frequency is critical to minimize data drift and ensure that the risk scores remain current. During the transformation phase, data cleansing is performed to handle missing values, rectify inconsistent entries in tender naming conventions, and filter out duplicated records. This daily routine ensures that the CACM system maintains high data integrity, which is a prerequisite for calculating accurate and reliable risk probability scores[11]. During the transformation phase, data cleansing is applied to maintain information quality and consistency. The processed data is then hosted on a cloud-based platform (Google Cloud Platform), which serves as the backend for the CACM dashboard, enabling real-time availability and scalability for audit purposes. This architecture enables the system to calculate weighted risk scores automatically, transforming complex database queries into intuitive graphical information for internal oversight units[12].

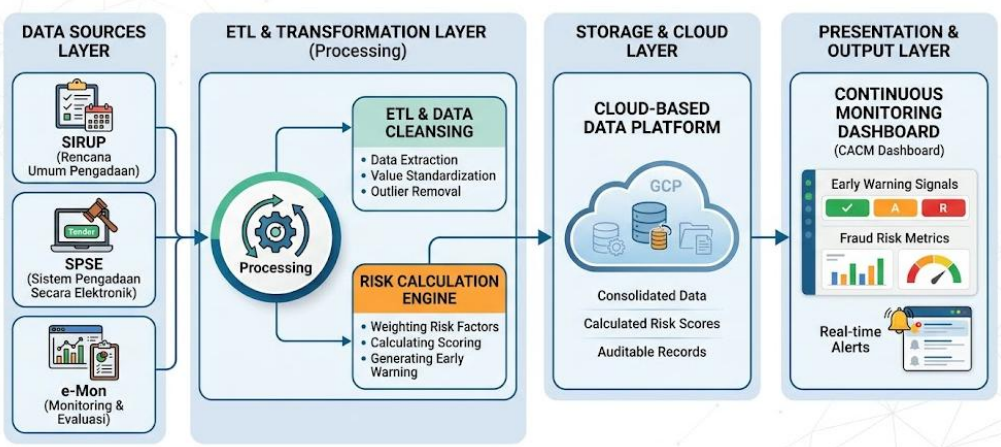

Figure 2. CACM System Architecture and Data Integration Workflow

The diagram is structured into four distinct horizontal layers:

1. Data Sources Layer: This layer identifies the primary data sources, specifically the procurement and monitoring systems (SIRUP, SPSE, and e-Mon).
2. ETL & Transformation Layer (Processing): This component serves as the core processing engine where raw data undergoes extraction, cleaning, and validation. It also houses the Risk Calculation Engine, which computes fraud risk metrics.
3. Storage & Cloud Layer: This layer represents the centralized repository where consolidated data is stored and managed on a cloud-based platform (GCP).
4. Presentation & Output Layer: This layer features the CACM Dashboard, which visualizes the processed information, providing early warning signals through a color-coded system (green, yellow, and red) to indicate risk levels.

2.3. Risk Detection Model and Mathematical Formulation

To enable automated anomaly detection, the CACM system utilizes a weighted risk scoring model. The cumulative risk score ($\mathbf{R}$) for each procurement package is calculated based on a set of risk indicators ($\boldsymbol{x}$) determined through historical data analysis. The mathematical equation used is as follows:

$$R = \sum_{n=1}^{n} (w_i . x_i) \qquad (1)$$

Where:

- ($\boldsymbol{R}$) is the total risk score for a single procurement package.
- ($\boldsymbol{w_i}$) is the relative importance weight for the *i*-th risk indicator.
- ($\boldsymbol{x_i}$) is the indicator variable value (assigned 1 if an anomaly is detected, and 0 otherwise)
- ($\boldsymbol{n}$) is the total number of monitored risk indicators.

2.4. Development Platform and Tools

The system prototype was developed using cloud computing technology to ensure scalability and real-time data accessibility. A data visualization platform was employed to transform complex database queries into intuitive graphical information for users within the internal oversight units.

3. RESULTS AND DISCUSSION

3.1. Historical Data Analysis and Risk Mapping

Prior to the implementation of the CACM system, an analysis of the procurement dataset from the 2016-2020 period was conducted to map risk patterns. The data extraction revealed a significant concentration of tender awards within a small group of partner entities. Table 1 presents the distribution of work packages among the top five partners with the highest winning frequency (data has been anonymized) and the remaining 51 partners categorized as 'Others'.

Table 1. Distribution of Tender Winner Concentration during the Observation Period

Partner Code	Number of Work Packages	Percentage of Total Packages (%)

Partner A	202	4,25
Partner B	173	3,64
Partner C	159	3,35
Partner D	144	3,03
Partner E	115	2,42
Others (51)	3.957	83,31
Total	4.750	100,00

The significant concentration of awards among specific partners (Partners A to E) serves as a primary parameter in the CACM system's risk detection engine. It is important to note that while this concentration is flagged as a risk indicator, it does not definitively prove collusion or fraudulent activity. High market concentration may occasionally arise from legitimate factors, such as niche specialization, high technical expertise, or superior competitive advantages within specific procurement categories.

The analysis demonstrates that the Selection Stage experienced the most significant surge in oversight effectiveness, increasing by 44% (from 30% to 74%). This can be attributed to the high density of structured digital data available during this specific stage within the SPSE (Electronic Procurement System). Unlike the Preparation or Handover stages, which often involve semi-structured documents or physical verification, the Selection Stage captures granular bidding data—including bidder identity, pricing, and technical evaluation scores—in a digitized format. Consequently, the CACM mathematical model can perform more accurate comparative analysis, such as detecting bid rigging patterns and price manipulation, which are significantly easier to quantify during the selection process than in other stages

Therefore, the CACM system is designed to provide an 'early warning' rather than a conclusive verdict. This approach is intended to mitigate the risk of false positives, as flagged anomalies serve as a signal for further investigation. Auditors are expected to exercise professional judgment to verify whether these detected patterns are the result of legitimate operational efficiency or if they indeed indicate potential procedural irregularities that require corrective measures.

3.2. CACM Dashboard Implementation

The developed system transforms raw data from existing platforms, such as procurement planning (SIRUP), electronic tendering (SPSE), and monitoring systems (e-Mon), into real-time visualizations. Based on testing during the integration phase, the system is capable of automatically processing oversight data with a broader scope and higher speed compared to traditional manual methods.

In addition to the cumulative score, the system calculates a fraud probability index P using a sigmoidal function to normalize the risk scores into a range of 0 to 1. This normalization aims to facilitate intuitive visualization on the monitoring dashboard:

$$P(\boldsymbol{R}) = \frac{1}{1 + e^{-R}} \qquad (2)$$

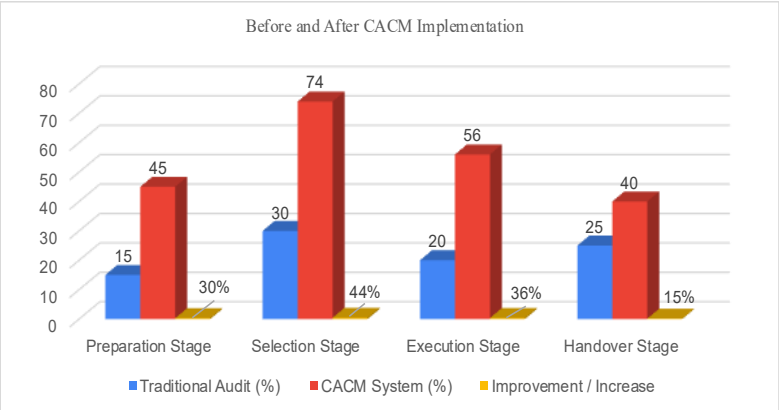

Figure 3. Comparison of Oversight Effectiveness Before and After CACM Implementation

Figure 3 illustrates a significant increase in oversight coverage across all stages of public procurement. The most substantial improvement is observed in the Selection Stage, where oversight effectiveness rose from 30% to 74%. This surge is attributed to the automated integration of SPSE data, which enables the system to perform real-time compliance checks on all tender packages. Such a task was previously difficult to execute manually due to the limited number of audit personnel relative to the high volume of procurement packages.[13]

The implementation focuses on four main procurement stages: preparation, selection, execution, and handover. System monitoring reveals that the effectiveness of oversight during the Selection Stage reached a data accuracy and coverage level of 74%, while the Execution Stage recorded 56%. This demonstrates that the CACM dashboard provides enhanced visibility for auditors, allowing for timely interventions at stages that historically carry the highest risks of procedural deviation [14].

3.3. Detailed Anomaly Discussion

The utilization of mathematical models and weighted risk scoring within this system enables instantaneous anomaly identification. The system specifically monitors patterns that indicate potential fraud, such as:

1. Winner Concentration: Automatically identifying if a specific group of partners wins a disproportionate number of packages, which may indicate a monopoly or lack of healthy competition.
2. Capacity Thresholds: Detecting when a partner wins work packages that exceed their Remaining Package Capacity (SKP), a key indicator of potential administrative or operational risk.
3. Document Similarities: Identifying identical bid document metadata or IP addresses among different participants, which strongly suggests collusion or horizontal bid-rigging [15].

Unlike previous studies that relied on static data, the CACM system in this research operates continuously through cloud platform integration (Google Cloud Platform). This infrastructure significantly reduces the audit reporting lead time from weeks to just a few days. Consequently, internal oversight units can implement corrective measures before contracts are finalized or payments are disbursed, effectively mitigating potential financial losses and strengthening institutional accountability [16].

3.4. System Validation (UAT)

The analysis reveals that the Selection Stage demonstrated the most substantial improvement in oversight effectiveness, rising by 44 percentage points (from 30% to 74%). This increase is primarily attributable to the high density of structured digital data available within the Electronic Procurement System (SPSE) during this phase. While the Preparation and Handover stages frequently rely on semi-structured documentation or manual verification, the Selection Stage captures granular bidding data (including bidder credentials), pricing, and technical evaluation scores (in a standardized digital format). Consequently, the CACM model facilitates more precise comparative analysis, enabling the effective detection of bid-rigging patterns and price manipulation, which are more readily quantifiable in the selection phase compared to other procurement stages[17].

4. CONCLUSION

This research successfully designed and developed an early warning system using Continuous Auditing and Continuous Monitoring (CACM) to enhance oversight in the public sector procurement process. Analyzing a comprehensive dataset of 4,750 work packages from 2016 to 2020, this study identified significant concentrations of awards, with the top five partners accounting for a substantial portion of tender wins, which serve as critical risk indicators for the CACM framework. The implementation of this system yielded a notable improvement in audit coverage across procurement stages, particularly in the Selection Stage, where oversight capability increased from 30% to 74%, representing a net improvement of 44%. It is necessary to clarify that the system functions as an automated, high-frequency monitoring tool rather than a live-streaming real-time system. By automating data ingestion, the system effectively mitigates the time lag inherent in manual data collection, allowing auditors to access and analyze risk metrics with minimal latency, thereby facilitating more timely interventions.

Despite these contributions, this study is subject to certain limitations. First, the current risk model relies primarily on frequency-based concentration metrics to identify potential collusion, which may generate false positives if competitive advantages are misinterpreted as anomalies. Second, the scope of this research is constrained to the 2016–2020 dataset, and the generalizability of the established risk thresholds may vary when applied to different procurement environments or smaller government agencies.

Based on these findings, future research should prioritize the transition from frequency-based thresholds to complex machine learning algorithms to enable the detection of multi-variable anomalies, such as price manipulation or collusion in technical specifications, thereby reducing the incidence of false positives. Furthermore, the CACM framework should be deployed across diverse government entities to validate its performance under varying procurement volumes and integrated directly with internal legal enforcement systems to ensure that flagged anomalies trigger an immediate, automated audit workflow. Finally, to maximize the utility of this system, technical implementation must be accompanied by comprehensive capacity-building initiatives for auditors. The system is designed to augment, not replace, professional judgment; thus, auditors must be adept at interpreting these early warnings to conduct evidence-based field verifications effectively.

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