



SECI and K-Means Integration for Public Sector Logistics Budget Efficiency

**Leiden Fauzi Yoka Surya^{1*}, R. Nyi Pipih Kurniasari², Muthia Ramadhani³,
Khansa Putri Amanda⁴, Ken Ditha Tania⁵, Dedy Kurniawan⁶, Ahmad Rifai⁷**

^{1,2,3,4,5,6,7}Department of Information System, Faculty of Computer Science,
Sriwijaya University, Indonesia

E-Mail: ¹09031282328043@student.unsri.ac.id, ²09031182328115@student.unsri.ac.id,
³09031182328013@student.unsri.ac.id, ⁴09031182328019@student.unsri.ac.id, ⁵kenya.tania@gmail.com,
⁶dedykurniawan@unsri.ac.id, ⁷ahmadrifai@ilkom.unsri.ac.id

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Corresponding Author: Leiden Fauzi Yoka Surya

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Abstract

Suboptimal management of office supplies causes significant budget waste in the public sector. This study addresses this issue by integrating the K-Means algorithm and the Socialization, Externalization, Combination, dan Internalization (SECI) knowledge management model to optimize logistics budget efficiency at the Palembang DPRD Secretariat. K-Means was utilized to partition the 2025 supply expenditure data into three priority clusters based on budget absorption and demand frequency. To ensure analytical outputs influence managerial decisions, K-Means was positioned as the primary explicit-to-explicit transformation engine within the SECI combination phase. The integration successfully transformed raw transaction data into a data-driven Standard Operating Procedure (SOP). Quantitative analysis reveals that a small subset of items in Cluster C3 accounts for a disproportionately high share of total budget absorption. Consequently, supervision can now strictly target these high-budget anomalies such as the Rp52.2 million spent on specific folio paper significantly reducing potential leakage and improving allocation efficiency. The main scientific contribution of this study is a novel framework that bridges mathematical data extraction and managerial policy formulation. This integrated approach is proven to measurably enhance regional budget efficiency.

Keywords: Budget Efficiency, Integrating, K-Means, Logistics, SECI

1. INTRODUCTION

The demand for accountability and budget efficiency in the public sector has driven government organizations to view operational data as a strategic asset [1]. Budget transformation through big data technology and digital governance has proven to be a determinant factor in improving the efficiency of regional financial management [2]. Organizations capable of managing knowledge systematically possess a competitive advantage in minimizing resource waste and fostering innovation [3], [4]. However, a crucial problem persists in government agencies, specifically at the Regional People's Representative Council (DPRD) Secretariat of Palembang City: procurement planning is heavily reliant on intuitive, assumption-based historical forecasting rather than empirical usage patterns [5]. This lack of data-driven governance frequently leads to severe budget inefficiencies, manifesting as either financial waste from overstocking or administrative paralysis from stockouts [6].

Addressing this complex problem requires a robust, data-driven approach. Data mining technology, particularly the K-Means clustering algorithm, offers an advanced analytical solution for extracting hidden behavioral patterns from massive inventory datasets [7], [8]. Recent studies explicitly highlight the efficacy of K-Means in public sector logistics and inventory segmentation, proving its precision in classifying high-priority procurement clusters without human bias [21], [22], [23]. These algorithmic outputs can be further optimized using validation techniques such as the Elbow method to ensure reliable priority profiling [9], [10], [11], [12]. Furthermore, comparative studies confirm that K-Means outperforms other clustering and classification models in organizing product inventory and operational logistics [24], [30].

Simultaneously, the Socialization, Externalization, Combination, Internalization (SECI) knowledge management model has demonstrated significant success in preserving institutional memory and dynamizing knowledge creation [13]. Recent literature underscores the critical role of knowledge management in public

administration, validating its ability to transform tacit bureaucratic intuition into formalized, transparent explicit policies and public innovation [25]. Furthermore, studies focusing on public sentiment and governance emphasize that combining digital data extraction with structured public policy evaluation directly correlates with measurable regional budget efficiency [26], [27], [28], [29].

Despite the massive individual adoption of data analytics and knowledge management, a critical research gap remains. The implementation of data analytics often fails to deliver tangible impacts because organizations lack a structural framework to convert mathematical insights into actionable managerial policies [18]. There is a distinct lack of literature that mechanically integrates an algorithm like K-Means as an explicit-to-explicit transformation engine directly within the SECI framework, particularly in the highly regulated public sector logistics environment [6], [19].

This research bridges that gap. The primary objective of this study is to propose and test an integrative framework that embeds K-Means clustering within the Combination phase of the SECI model to restructure public sector logistics governance. This synergy is expected to preserve operational knowledge while continuously validating it against objective data, thereby transforming logistics governance into a measurable, efficient, and transparent system [20].

2. RESEARCH METHODOLOGY

This study employs a mixed-methods approach to restructure public sector logistics governance. To ensure reproducibility, the research workflow integrates the Knowledge Discovery in Databases (KDD) framework for data extraction with the Socialization, Externalization, Combination, Internalization (SECI) model for managerial policy formulation.

2.1. Theoretical Foundation and Method Justification

Before executing the data extraction, it is necessary to establish the theoretical framework that justifies the method selection.

1. K-Means Clustering in Logistics: K-Means is an unsupervised machine learning algorithm that partitions n observations into k clusters based on the nearest mean. In inventory management, K-Means is theoretically favored over traditional ABC analysis because it does not rely on rigid, predetermined thresholds. Instead, it dynamically identifies natural groupings within empirical data (such as budget volume and order frequency), providing a highly objective foundation for inventory segmentation.
2. The SECI Model: Developed by Nonaka and Takeuchi, the SECI model theorizes that organizational knowledge is created through interactions between tacit and explicit knowledge. In the public sector, where employee turnover disrupts institutional memory, SECI provides a rigorous framework to capture and standardize operational intuition into formal governance structures.
3. Justification for Integration: While K-Means excels at uncovering quantitative patterns, it lacks the theoretical capacity to enforce human adoption. Conversely, the SECI model focuses on human interaction but often lacks objective mathematical validation in its 'Combination' phase. Therefore, this study integrates K-Means directly into the Combination phase, ensuring that explicit data is mathematically optimized before being internalized into Standard Operating Procedures (SOPs).

To systematically illustrate the research flow, the methodology is divided into three main consecutive phases as depicted in the research workflow (Figure 1).

2.2. Materials and Data Preparation

The primary material utilized in this study is empirical secondary data obtained directly from the Regional People's Representative Council (DPRD) Secretariat of Palembang City. The dataset comprises the actual recapitulation of office stationery inventory and expenditure transaction records for the complete 2025 fiscal year [5].

During the preparation phase, raw data collected from transaction logs were systematically cleaned by removing incomplete records, noise, and outliers [12]. The dataset was then aggregated to obtain two precise computational variables: Total Budget Absorption (measured in millions of Rupiah) and Demand Frequency (measured in single digits). Given the drastic scale difference between these two variables, data normalization was strictly required to prevent distance calculation distortions. The Min-Max Scaling technique was applied to transform the data features into a standard range of 0 to 1, using the following equation 1.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where X_{norm} represents the normalized data, X is the original data value, and X_{min} and X_{max} are the minimum and maximum values of the feature, respectively.

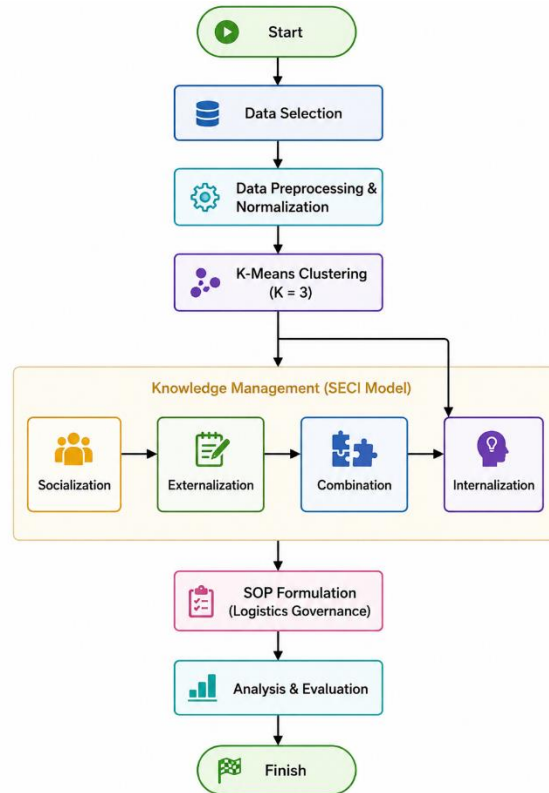


Figure 1. Research Methodology

2.3. Proposed Model: K-Means Clustering Execution

The core analytical method employed is the K-Means algorithm, utilized for comparing and clustering the normalized historical data. The objective of this method is to partition n observations into k clusters based on usage pattern characteristics [8]. To measure the similarity between continuous variables (budget and frequency), the Euclidean distance metric was selected. The distance between a data point (x) and the centroid (c) is calculated as follows (equation 2).

$$d(x, c) = \sqrt{\sum_{i=1}^n (x_i - c_i)^2} \quad (2)$$

The algorithm iteratively reassigns data points to the nearest centroid to minimize the objective function, known as the Within-Cluster Sum of Squares (WCSS), equation 3.

$$J = \sum_{j=1}^k \sum_{i=1}^n ||x_i^{(j)} - c_j||^2 \quad (3)$$

To evaluate and determine the optimal number of clusters (k), the Elbow Method was employed [11]. Based on the inflection point of the inertia curve, the model was evaluated to use $k = 3$, effectively segmenting the data into high, medium, and low priority profiles.

2.4. Knowledge Management Integration (SECI Framework)

Mathematical models often fail if not adopted by the organization's human resources. Therefore, the proposed framework integrates the K-Means output directly into the 4 phases of the SECI knowledge creation cycle [14]:

1. Socialization: The sharing of tacit knowledge among logistics staff through direct interactions regarding daily operational complaints and budget ambiguity.
2. Externalization: The articulation of staff tacit knowledge into explicit knowledge through the formalization of structured item expenditure spreadsheets (Log Books).
3. Combination (The Integration Point): The systematic process of combining explicit data into strategic new knowledge. The predetermined K-Means algorithm acts as the primary enabler in this phase, mechanically transforming raw datasets into objective, explicit classifications (e.g., separating high-value anomalies from routine supplies) without human bias.

4. Internalization: The transformation of explicit computational results back into new tacit knowledge. Leadership absorbs these data-driven classifications to formulate and enforce definitive logistics procurement SOPs.

3. RESULTS AND DISCUSSION

3.1. K-Means Algorithm Clustering Result

The analytical process commenced with determining the optimal number of cluster (k) for the 2025 inventory dataset. By evaluating the Within-Cluster Sum of Squares (WCSS), the Elbow Method visualization (Figure 2) demonstrates a significant drop in inertia, forming an inflection point at $k = 3$. Consequently, the algorithm was set to partition the data into three priority profiles.

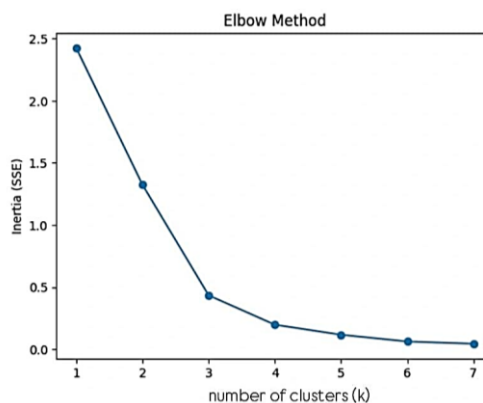


Figure 2. Elbow Method for Determining Optimal Number of Clusters (k)

Following the convergence of the K-Means algorithm, the dataset of office stationery was segmented based on demand frequency and total budget absorption. Table 1 presents a factual snapshot of the top items classified by the algorithm's output, separating massive expenditures from routine operational requests.

Table 1. K-Means Clustering Result of Office Stationery (Top 15 Items)

No	Item Name	Total Budget (Rp)	Demand Frequency	Priority Category (Cluster)
1	HVS Folio Paper 70gr Sinar Dunia	52,200,037	15 Times	C3 (High Budget)
2	HP Laser Jet Toner	12,600,002	32 Times	C1 (Fast-Moving)
3	DPRD Official Receipt	9,675,008	11 Times	C1 (Fast-Moving)
4	DPRD Block Note	8,251,142	7 Times	C1 (Fast-Moving)
5	Mail Control Card	7,840,000	26 Times	C1 (Fast-Moving)
6	Flash Drive 4GB Kingston	7,800,004	26 Times	C1 (Fast-Moving)
7	HVS Quarto Paper 70 gr	6,784,007	45 Times	C1 (Fast-Moving)
8	Mail Agenda Book	6,200,000	26 Times	C1 (Fast-Moving)
9	Tissue Paper	5,775,009	25 Times	C1 (Fast-Moving)
10	DPRD Letterhead	5,636,000	1 Time	C1 (Fast-Moving)
11	DPRD Logo Letterhead	5,635,950	24 Times	C1 (Fast-Moving)
12	HVS A3 Paper 60 gr	5,250,005	1 Time	C1 (Fast-Moving)
13	Brother Color Ink Refill	4,900,006	11 Times	C1 (Fast-Moving)
14	HVS A4 Paper 70 gr	4,845,006	41 Times	C1 (Fast-Moving)
15	Brother Black Ink Refill	4,750,004	30 Times	C1 (Fast-Moving)

3.2. Validation and Numerical Budget Effectiveness

The application of the Elbow Method successfully validated the clustering model, distinctly separating expenditures into actionable tiers. Numerical analysis of the clusters reveals severe disparities in budget absorption. Cluster C3 objectively isolated extreme financial anomalies. For instance, the system identified "HVS Folio Paper" absorbing a massive Rp52,200,037 despite a relatively low demand frequency (15 times). This indicates that a fraction of inventory items consumes a highly disproportionate percentage of the budget. Conversely, Cluster C1 (Main Operational / Fast-Moving) dominates the administrative pulse. Items like "Laser Jet Toner" and "Quarto Paper" exhibit intense request frequencies (up to 45 times) with moderate individual costs. Recognizing these numerical realities is vital for budget effectiveness; stockouts in C1 paralyze public service operations, while unsupervised procurement in C3 leads to catastrophic budget leakage. Cluster C2 contains the majority of minor items with negligible budget impact, allowing for simplified procurement.

3.3. Discussions: Connecting Findings to SECI Theory and Prior Studies

Unlike previous studies that solely utilize algorithms to display data segments, this study theoretically operationalizes the mathematical findings through the SECI cycle, deeply connecting data analytics with organizational behavior:

1. Socialization & Externalization: Informal, tacit complaints regarding budget ambiguity were systematically standardized into explicit transaction logs, effectively translating tacit intuition into explicit data ready for mining.
2. Combination (The Novelty): The explicit raw logs were processed by the K-Means algorithm. This step replaces traditional human-led data combination with mathematical precision, objectively separating high-value items (C3) from routine supplies (C1/C2) and removing bureaucratic bias.
3. Internalization & Governance Implications: The quantitative clustering results were actively internalized by leadership to enforce a new data-driven governance paradigm.

The practical implication for public governance is profound. By trusting the mathematical output, the Palembang DPRD Secretariat fundamentally restructures its logistics governance from a rigid, assumption-based system to a dynamic model. A "Multi-Tier Approval System" is now strictly enforced for the C3 cluster, requiring rigorous cross-departmental justification to prevent overstocking. Conversely, C1 items utilize an automated Re-Order Point (ROP) system with minimized bureaucracy to prevent operational disruption. This continuous SECI cycle ensures that the analytical capability is cultivated as a shared organizational culture, sustainably safeguarding regional financial integrity.

3.4. Managerial Implications and Governance Transformation

The final discussion addresses the overarching research question: how this integration improves budget efficiency. The implementation fundamentally restructures the Palembang DPRD Secretariat's logistics governance from a rigid, assumption-based system to a dynamic, transparent model.

By trusting the system's output, a "Multi-Tier Approval System" is now strictly enforced for the C3 cluster. Procurements in this category require rigorous cross-departmental justification to prevent overstocking. Conversely, the managerial implication for the C1 cluster is the implementation of an automated Re-Order Point (ROP) system with minimized bureaucracy to prevent operational disruption. Ultimately, this continuous SECI cycle ensures that the analytical capability is not isolated within an IT department but cultivated as a shared organizational culture, sustainably safeguarding regional financial integrity.

4. CONCLUSION

This research successfully demonstrates that public sector logistics inefficiencies can be systematically resolved by integrating K-Means clustering with the SECI knowledge management model. The primary scientific contribution is the novel positioning of the K-Means algorithm as the objective data-enabler within the Combination phase of the SECI cycle. This methodological synergy effectively converted raw, unstructured transaction data into a highly structured, three-tier priority matrix. Consequently, the institution transitioned from assumption-based procurement to a data-driven governance model, formulating explicit SOPs that impose strict financial supervision on high-budget anomalies (Cluster C3) while streamlining routine operational supplies (Cluster C1).

To strengthen future academic contributions, it is highly recommended that subsequent studies employ longitudinal data spanning multiple fiscal years to evaluate the long-term stability of the clusters. Furthermore, incorporating predictive analytical techniques, such as Time-Series forecasting or Deep Learning algorithms, could transition the inventory management model from a reactive classification system to a fully proactive, predictive governance framework.

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