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Implementation of K-Medoids Clustering Method for B2B Service Price Segmentation at PT Telkom Tasikmalaya

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ABSTRACT

PT Telkom Indonesia Witel Tasikmalaya faces strategic challenges in monitoring customer behavior in real-time and determining optimal Business-to-Business (B2B) service pricing strategies due to conventional data management. This study aims to design a Web-based Decision Support System to analyze B2B service pricing using the K-Medoids clustering algorithm with Manhattan Distance metrics. The research and system development are fully structured using the Agile methodology. The model evaluation is measured using the Davies-Bouldin Index. The data mining modeling indicates that the formation of three clusters is the most optimal partition with the smallest Davies-Bouldin Index value of 0.638. The clusters successfully map customer profiles from small enterprises to large corporations as a baseline price recommendation. The system is built using an implementation of vanilla JavaScript and Google Firebase serverless architecture, achieving success in functional black-box testing and a 90% score in user acceptance testing. This research provides a strategic contribution by accelerating the issuance of quotation documents and optimizing company revenue.
Keywords: Agile Methodology; Customer Monitoring; Davies-Bouldin Index; K-Medoids Clustering; Revenue Optimization

INTRODUCTION

PT Telkom Indonesia Witel Tasikmalaya faces strategic challenges in establishing competitive service pricing for Business-to-Business (B2B) customer segments. The contemporary dynamics of the telecommunications industry require companies to adopt information systems that seamlessly integrate sales performance oversight with long-term data analytics (Alexandes et al., 2022; Rodriguez & Boyer, 2020; Sunendar, 2025). Conventional pricing approaches often fail to represent the optimal willingness to pay because the revenue generated from B2B clients features highly significant variance, stretching from small micro-enterprises to large-scale corporations. This financial demographic condition inherently produces datasets with extreme outliers that can disrupt traditional prediction formulas (Hermansah et al., 2025).

To overcome the data imbalance caused by these extreme financial outliers, the K-Medoids algorithm serves as one of the most robust clustering methods by assigning actual data objects as cluster centers (Dinata et al., 2021; Fahrudin & Rindiyani, 2024; Sela et al., 2025). Although previous studies regarding telecommunication customer segmentation are numerous (Sulistyawati & Sadikin, 2021), most prior works focus solely on static consumer data analysis without integrating it into an operational system accessible to the sales team (Hutagalung et al., 2022).

This research aims to bridge this structural gap by implementing the K-Medoids clustering results directly into an active Web-based Decision Support System. This integration is designed not only to provide real-time baseline pricing recommendations but also to facilitate the monitoring of strategic business metrics, such as customer retention and lifetime value, to optimize enterprise revenue.

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LITERATURE REVIEW

Customer segmentation analysis across multiple industrial fields has been heavily explored to enhance operational marketing efficiency and targeted resource distribution (Kamalia & Nawangsih, 2025; Ramayanti et al., 2023)In the telecommunications context, a foundational approach by Hutagalung et al. (2022) successfully applied the K-Medoids algorithm to partition B2C retail internet services based on regional transaction data. However, this study distinctly targets B2B client portfolios, which are characterized by massive revenue variances that shift drastically compared to retail consumers (Linarti et al., 2024). For such corporate financial datasets, the K-Medoids algorithm, particularly when combined with the Manhattan Distance metric, empirically proves to be far more robust against extreme outliers (Hermansah et al., 2025; Sela et al., 2025; Solikhun et al., 2025).

Despite the computational accuracy demonstrated in prior clustering works, a significant research limitation persists: the separation between data mining execution and live software deployment. Most previous data mining models operate as static analytical experiments executed within localized environments or rely on rigid evaluation structures (Handono et al., 2025; Silvya et al., 2020), meaning their results remain confined to offline reports and cannot be immediately utilized by field personnel during active client negotiations.

This research effectively resolves this gap by translating the core medoid points extracted from the B2B cluster partition directly into an active Web-based Decision Support System (Anwar, 2026; Krisnamurti et al., 2025; Risma et al., 2026). By leveraging serverless cloud infrastructure (Erike et al., 2025; Fati & Alenezi, 2024) and interactive analytical dashboard design principles (Ni'mah et al., 2024), this system transforms passive data clustering into a real-time decision support architecture designed for immediate corporate utility.

METHOD

This research applies a quantitative approach to process B2B operational data using clustering algorithms. To ensure the software engineering process remains highly adaptive to the dynamic needs of the sales team, the entire research workflow is structured under the Agile Development methodology. This framework integrates both data mining operations and web application development across six iterative phases:

Figure 1. Agile Method

Planning

This initial phase focuses on requirement gathering through interviews with Sales Engineers to establish the product backlog, alongside the extraction of historical B2B customer transaction datasets (specifically bandwidth capacities and monthly revenue values).

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Implementation (Core Phase)

This phase executes both data processing and system coding simultaneously. The raw B2B dataset undergoes Min-Max Scaling to normalize the extreme financial variances. Following this, the K-Medoids algorithm is executed using the Manhattan Distance metric. Manhattan distance provides a linear measurement that stabilizes the algorithm against massive revenue anomalies, unlike Euclidean distance which exaggerates extreme values. The algorithm was set to $k = 3$ clusters, explicitly justified by the enterprise's strategic need to categorize clients into low-tier, mid-tier, and high-tier business segments. Concurrently, the frontend web application is constructed using HTML5, vanilla JavaScript, and Tailwind CSS.

Software Testing

The outputs from the implementation phase are evaluated through three parameters. First, structural cluster validation is measured using the Davies-Bouldin Index (DBI). DBI was specifically selected because it evaluates both intra-cluster cohesion and inter-cluster separation, where a lower index value mathematically guarantees an optimal group structure. Second, functional system validation is conducted via Black Box Testing. Third, operational feasibility is evaluated through User Acceptance Testing (UAT).

Documentation

The validated medoid coordinates are extracted and documented to formulate baseline pricing strategies. Additionally, the system is programmed to automatically generate and export official quotation documents (PDF/Excel).

Deployment

The integrated Web-based Decision Support System is deployed into a live production environment using a Google Cloud Firestore serverless architecture to handle real-time data synchronization and high concurrency.

Maintenance

The final phase involves post-release evaluation and adjusting the Weighted Moving Average (WMA) forecasting parameters to maintain system accuracy against future business trends.

RESULT

Planning Phase

The initial phase involved identifying operational requirements and extracting the raw Business-to-Business (B2B) transaction dataset from the PT Telkom Witel Tasikmalaya corporate repository. Following the filtering of non-active accounts, 114 active enterprise examples were selected as the primary dataset for clustering.

Table 1. B2B Transaction Dataset Profile

No.	Nama Pelanggan	PIC	Status	Layanan	Kelurahan	Revenue
1	P1	RKS	Aktif	Indihome	Empangsari	285000
2	P2	SR	Non-Aktif	Indihome	Ciherang	285000
3	P3	RKS	Prospek	HSI Bisnis	Empangsari	347000
4	P4	AA	Aktif	Indihome	Cilembang	275000
5	P5	RKS	Aktif	Antares Eazy	Panglayungan	449000
6	P6	WM	Aktif	HSI Bisnis	Empangsari	819000

Requirement analysis with the sales engineering team established the necessity for an automated baseline pricing calculator, real-time spatial mapping, and a dynamic analytical dashboard to optimize revenue tracking.

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Implementation Phase (Data Mining and System Construction)

This core phase executed both the mathematical modeling and the software coding simultaneously. First, the bandwidth and revenue variables underwent a preprocessing transformation using Min-Max Scaling to achieve uniform numerical scaling between 0 and 1, preventing extreme corporate revenue variances from dominating the spatial calculations.

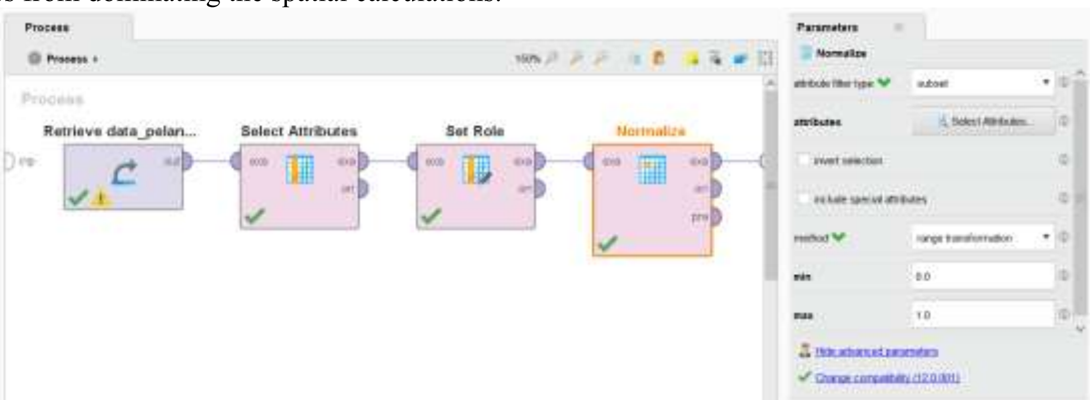

Figure 2. Preprocessing And Data Normalization Operator Setup in Altair AI Studio

Next, the K-Medoids algorithm was executed. To handle extreme outliers effectively, the proximity between data points was calculated using the Manhattan Distance metric, which is formulated as follows:

$$d(x,y) = \sum_{i=1}^{n} |x_i - y_i|$$

Information:
$d\ (x,y)$ = Distance of data to x to center of cluster y.
n = number of attributes used.
$x_i\ , y_i$ = Data to x, y on attributes data to-i.

The algorithm evaluates object proximity iteratively to minimize the absolute error criterion (E), seeking the most optimal actual data objects (medoids) across a predefined cluster parameter of $k = 3$. The cost function (Absolute Error Criterion) is defined as:

$$E = \sum_{j=1}^{k} \sum_{p \in C_J}^{k} d(p, o_j)$$

Information:
.E = Total absolute deviation (Absolute Error Criterion).
k = Total number of desired clusters.
p = Data object within cluster C_j.
o_j = Representative data object (Medoid) of cluster C_j.
$d(p, o_j)$ = Distance between object p and medoid o_j.
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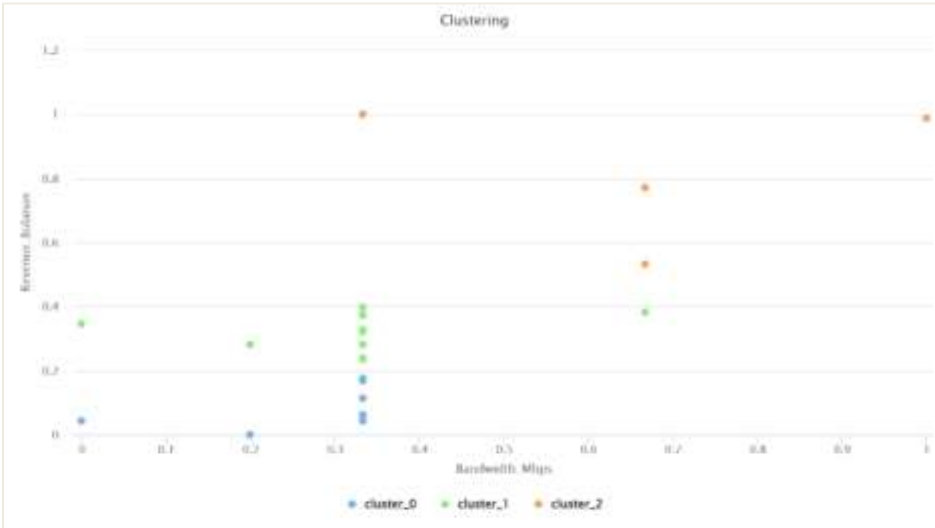

Figure 3. K-Medoids Clustering Scatter Plot Visualization

Concurrently, the frontend application of the Web-based Decision Support System was built using HTML5, vanilla JavaScript, and Tailwind CSS to ensure a lightweight and highly responsive user interface. The relational structure was mapped utilizing Unified Modeling Language components, leading to the creation of the database logic.

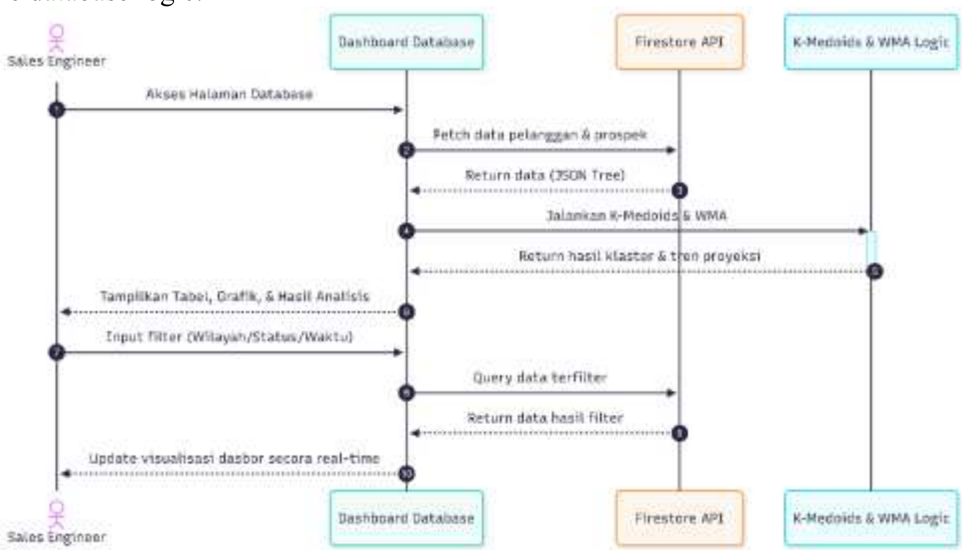

Figure 4. Sequence Diagram of the Continuous Cloud-Sync Data Integration Pipeline

To present this automated analytical pipeline to regional management teams, a centralized system dashboard was constructed. The production user interface of the proposed system is shown in Figure 7.

Software Testing Phase

To evaluate the outputs of the implementation phase, rigorous testing was conducted across three parameters. First, the structural quality of the K-Medoids clusters was mathematically validated using the

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Davies-Bouldin Index (DBI). The DBI metric measures the ratio of intra-cluster dispersion to inter-cluster separation, which is mathematically formulated as follows:

$$DBI = \frac{1}{k}\sum_{i=1}^{k} \max_{j \neq i}\left(\frac{s_i + s_j}{d_{ij}}\right)$$

Information:

k = Total number of clusters.

S_i, S_j = Average dispersion (distance) of all data objects within cluster i and cluster j to their respective medoids.

d_{ij} = Distance between the medoid of cluster i and the medoid of cluster j.

The execution yielded a highly optimal DBI score of 0.638, confirming tight intra-cluster variance and distinct inter-cluster separation.

Table 2. Cluster Validity and Distance Performance Metrics

Performance Evaluation Component	Altair AI Studio Metric	Proximity Interpretation
Average distance within centroid (Cluster 0)	0.002	Highly Compact
Average distance within centroid (Cluster 1)	0.023	Compact / Dense
Average distance within centroid (Cluster 2)	0.094	Compact / Dense
Davies-Bouldin Index (DBI)	0.638	Optimal Cluster / Valid

Second, functional validation via Black Box Testing confirmed that all integrated system features including the pricing calculator and dynamic visualizations operated flawlessly. Third, a User Acceptance Test (UAT) administered to the regional management team yielded a 90% feasibility score, categorizing the system as highly acceptable for live operations.

Documentation Phase

The outputs of the algorithm were extracted and documented to define the enterprise's strategic baseline. The system extracted the central medoid coordinates of the three distinct customer segments: Low-Tier (Cluster 0), Mid-Tier (Cluster 1), and High-Tier (Cluster 2).

Table 3 Medoid Coordinates and Centroid Centric Profiles

Cluster ID	Segment Tier Classification	Medoid Bandwidth	Medoid Revenue
Cluster 0	Low-Tier Customers	0.000	0.015
Cluster 1	Mid-Tier Customers	0.111	0.061
Cluster 2	High-Tier Customers	0.444	0.407

These validated constants act as the algorithmic baseline rules for B2B contract negotiations. Additionally, the system was programmed to automatically document these calculations by generating exportable official quotation files (PDF and Excel format) for the field sales operations.

Deployment Phase

To transition the analytical models into a production-ready system, the web application was deployed using a serverless cloud infrastructure. Specifically, the platform utilizes the Google Firebase Firestore API to handle relational JSON structural trees dynamically.

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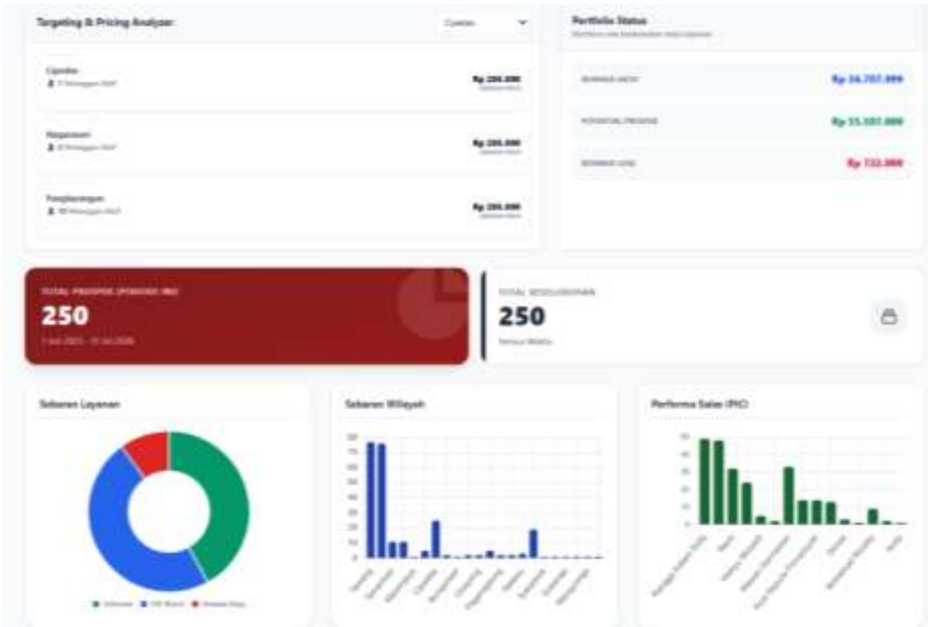

Figure 5. The Production Interface of the Web-based Decision Support System

This NoSQL integration effectively eliminates data pipeline latency, facilitating high-concurrency access and providing real-time synchronization for the dashboard visualizations across all sales engineer endpoints.

Maintenance Phase

The final phase establishes post-deployment stability. The system is designed to allow continuous data updates and periodic recalibration of the Weighted Moving Average (WMA) forecasting parameters to ensure the predictive analytics adapt fluidly to shifting regional corporate network demands and future market trends.

DISCUSSIONS

Algorithmic Performance and Methodological Contribution

The empirical results generated through the integration of the K-Medoids clustering algorithm provide significant structural insights into B2B market segmentation. Methodologically, this study demonstrates that utilizing actual data points as medoids—rather than mathematical averages—successfully isolates extreme financial outliers inherent in corporate datasets. Evaluated via the Davies-Bouldin Index (DBI), the model achieved an optimal score of 0.638, confirming high intra-cluster homogeneity and distinct inter-cluster separation. This proves mathematically that the algorithm prevents revenue dilution in strategic planning by distinctly separating high-yield corporate accounts from dense mass-market retail subscriptions.

Strategic Commercial Implications and Dashboard Utility

The extraction of specific medoid coordinates provides a robust practical blueprint for operationalizing Customer Relationship Management (CRM) and restructuring corporate tariff matrices:

a. Cluster 0 (Mass Segment), accounting for the majority of the customer base, this segment demands high infrastructure volume but yields narrow profit margins. The optimal commercial intervention

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focuses on Mass Penetration Pricing through scalable digital service bundling to maintain basic customer retention.

b. Cluster 1 (Growth Segment), this group presents volatile bandwidth usage but stable revenue streams. Strategically, this segment is highly receptive to Value-Based Pricing, where premium add-ons (e.g., cloud backup or cybersecurity) can be up-sold to significantly maximize Customer Lifetime Value (CLV).
c. Cluster 2 (Premium Segment), though making up the smallest percentage of accounts, this segment is financially critical. Management must deploy Premium Pricing paired with strict Service Level Agreements (SLAs) and dedicated 24/7 technical Account Managers to prevent escalating compound churn rates.

To ensure these mathematical insights translate into operational efficiency, the deployment of the Web-based Decision Support System serves as the primary practical contribution of this research. By adhering to strong dashboard design principles and ensuring strict visual consistency across its tracking matrices, the platform allows sales engineers to instantly interpret complex clustering results and monitor real-time business dynamics without requiring deep data science expertise.

Limitations of the Study

Despite its comprehensive theoretical and practical contributions, this study possesses certain limitations. The clustering model was developed using a localized dataset geographically confined to the PT Telkom Witel Tasikmalaya region, relying on a limited scope of 114 active enterprise. Furthermore, the clustering attributes were restricted to bandwidth capacity and monthly revenue. Future research should expand the data volume across wider regional territories and incorporate temporal tracking variables to facilitate long-term behavioral forecasting.

CONCLUSION

This research successfully demonstrates a closed-loop business intelligence framework that bridges unsupervised machine learning with production cloud architectures. By utilizing the K-Medoids algorithm on 114 active B2B at PT Telkom Witel Tasikmalaya, the system achieved a highly optimized and mathematically validated grouping structure consisting of three customer tiers (k=3), backed by a robust Davies-Bouldin Index score of 0.638.

The implementation of the proposed analytics platform proves that complex algorithmic clustering can be effectively decentralized and delivered directly to non-technical stakeholders via dynamic web dashboards. The real-time mapping of service tracking, regional density matrices, and individual sales account matrices enables the enterprise to move beyond rigid, generalized tariff plans.

Ultimately, this data-driven framework allows the company to deploy precise, automated pricing models, maximize potential revenue pipelines, and minimize client churn across distinct regional sectors. Future expansions of this model will explore the inclusion of historical churn metrics and real-time network traffic logs to further refine the predictive capabilities of the clustering engine.

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