



Application Of K-Means Clustering Method For Stock Grouping In Nobita Eyewear Store Inventory System

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ABSTRACT

Inventory mismanagement can lead to overstocking of slow-moving items and stockouts of high-demand products. This study aims to develop a web-based inventory information system at Nobita Eyewear Store that integrates K-Means Clustering to group stock based on historical sales data. The dataset consists of 308 transactions from January to April 2026 across 113 product types. Stock, purchase price, total inbound, and total outbound attributes were normalized using Min-Max Normalization. The optimal number of clusters was determined using the Elbow Method and validated using the Silhouette Score, Davies-Bouldin Index, and Calinski-Harabasz Index. The system was developed using Laravel and SQLite with the waterfall method. The results show that K=3 is optimal, converging at the fifth iteration and producing very fast-moving, fast-moving, and slow-moving categories. Black Box Testing confirmed that all features functioned as required. A User Acceptance Test with 30 respondents yielded an 89% acceptance rate, categorized as very good. The system helps Nobita Eyewear Store prioritize stock more objectively. Research limitations are discussed for future development.

Keywords: Elbow Method; Inventory Information System; K-Means Clustering; Laravel; Stock Grouping

1. INTRODUCTION

Smooth business operations depend heavily on accurate inventory management. Poorly organized stock management can lead to the accumulation of certain product categories and shortages of high-demand products. An inventory information system is a strategic solution because it supports data accuracy and improves decision-making quality [1]. Nobita Eyewear Store is located on Jl. Pemda, Pangkalan Kerinci. The store provides various optical products, such as frames, lenses, and accessories. Inventory is still managed uniformly, without grouping products according to sales levels. As a result, the store has difficulty identifying products with high and low sales. Stock prioritization is still determined based on the owner's experience.

K-Means Clustering is a non-hierarchical data mining technique. This method groups data based on their proximity to a central point or centroid. The process is performed repeatedly until a stable condition is achieved [2]. This method was selected because its computation is relatively simple and it can group products based on similarities in their characteristics. Several previous studies have applied K-Means to inventory and sales data. Afiasari et al. applied K-Means to sales transaction data to identify product groups based on similar characteristics [2]. Ghofur et al. applied K-Means to determine inventory stock at Toko At-Thullah Tuban [3]. Karsa and Hidayat applied K-Means to group the best-selling products at Toko Tono Grosir [4]. Rizki and Mulyawan applied K-Means to sales data at Optik Chantika [5]. Hardianto et al. used K-Means to determine stock-item categories at Angkasa Mart [6], while Nugraha et al. applied the method to analyze sales at Yana Sport Store [7]. These studies demonstrate the use of K-Means for grouping products; however, the integration of clustering results into an operational inventory system remains an important aspect to be developed.

The novelty of this study lies in the direct integration of clustering results into the daily inventory system. The clustering process runs automatically whenever stock changes occur, without manual

intervention. The optimal number of clusters is determined using the Elbow Method and validated through the Silhouette Score, Davies-Bouldin Index, and Calinski-Harabasz Index. The results are then used to classify products into three categories: very fast-moving, fast-moving, and slow-moving. This approach is expected to support more objective stock-priority decisions.

Based on this description, K-Means has been widely applied to group products in various business sectors. However, these implementations are generally still manual, and clustering results are presented separately from the operational inventory system. This study addresses this gap by integrating K-Means Clustering into a web-based inventory information system, enabling stock grouping to be updated automatically according to changes in transaction data.

This study aims to develop a web-based Inventory Information System at Nobita Eyewear Store that integrates the K-Means Clustering method to group inventory based on historical sales data. The optimal number of clusters is determined using the Elbow Method and validated through the Silhouette Score, Davies-Bouldin Index, and Calinski-Harabasz Index. The system is expected to assist store management in determining stock priorities based on more objective data.

2. RESEARCH METHODS

2.1. Data Collection Phase

Data collection was carried out through observations of the ongoing inventory management and recording processes, as well as interviews with the owner and staff of the Nobita Eyewear Shop. These activities were conducted to gather information regarding system requirements, inbound and outbound goods recording processes, stock management, and inventory data, which serve as the foundation for system design and the application of the K-Means Clustering method. Additionally, data collection involved a literature study by reviewing scientific journals relevant to inventory systems, stock management, and the K-Means Clustering method. The literature study aimed to establish a theoretical foundation, understand the implementation phases of the K-Means Clustering method, and serve as a reference in designing and developing the inventory system at the Nobita Eyewear Shop.

2.2. System Development Phase

This study adopts the Waterfall model as the primary framework for the research and system development phases. The Waterfall method was selected due to its systematic, structured, and easy-to-understand workflow. Generally, the research phases in the Waterfall method consist of several main stages: requirement analysis, system design, implementation, testing, and maintenance.[10] .

A. Requirement Analysis

In this phase, the problems faced were identified, research objectives were established, and the requirements for the system to be developed were determined. Information gathering focused on the inventory recording process and the need for stock clustering based on sales levels at the Nobita Eyewear Shop. The collected data included item profiles, sales transaction data, as well as functional and non-functional system requirements to support the design of a targeted solution..

B. System Design

In this phase, the analyzed requirements are translated into a system design blueprint. The design encompasses the architectural design and the process workflow design.

1. Architectural Design

The developed system architecture illustrates the relationship between the users, the web browser, the Laravel-based web server, and the SQLite database.

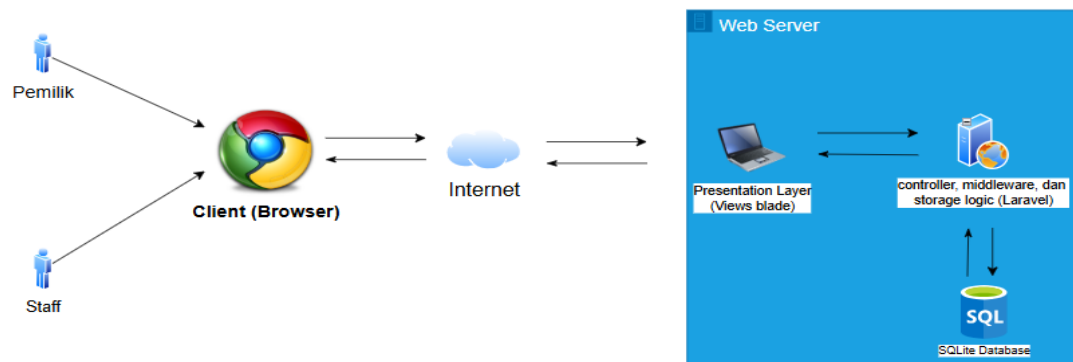


Figure 1. Architectural Design

The Inventory System Architecture of Nobita Eyewear Shop illustrates the communication mechanism between users and the web-based system. The system is accessed by two types of users the Owner and the Staff via a client (browser) connected to the internet, directing requests to the web server where the application is hosted. Within the web server, user requests are processed at the Application Layer through middlewares, routes, controllers, and models. This process interacts with the Data Layer, utilizing an SQLite Database for data storage and retrieval. Subsequently, the controller forwards the processing results to the Presentation Layer, which employs Blade as a template engine to render the data into HTML pages before displaying them back to the users through the browser according to their respective access privileges.

2. Use Case Diagram Design

Use Case Diagram illustrates the interactions between users (actors) and the system, as well as the functions accessible to each actor. This diagram provides a general overview of what the system can perform from the user's perspective [10].

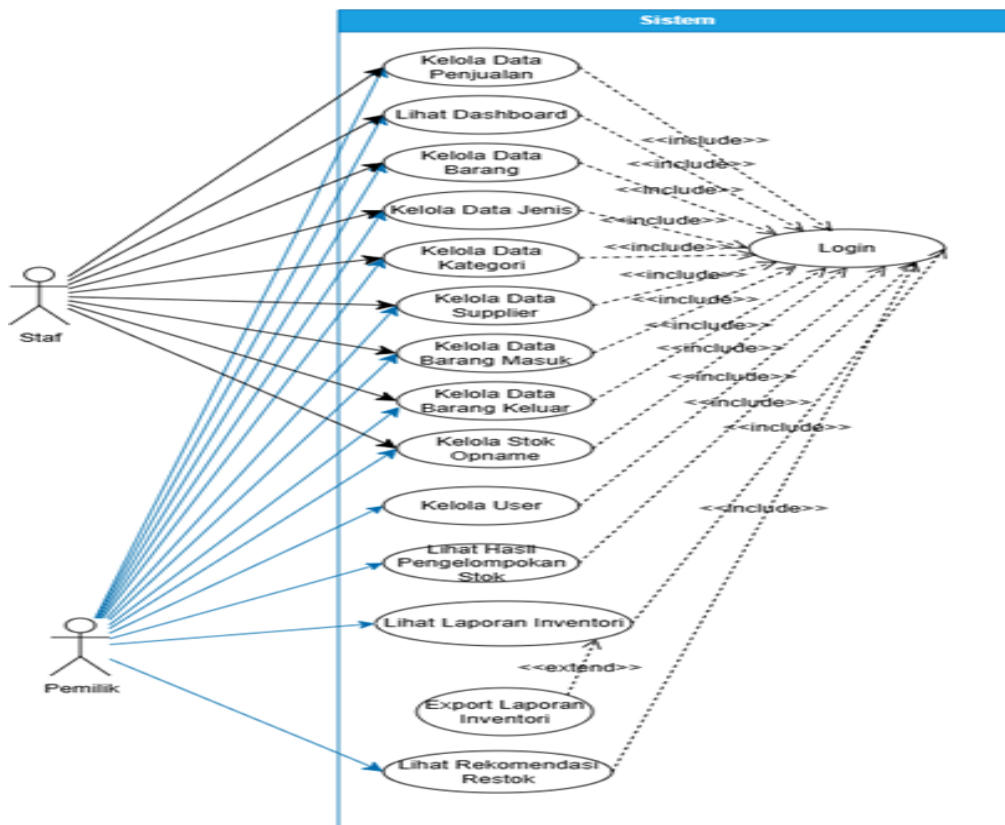


Figure 2. Use Case Diagram

C. Implementation (Coding)

The implementation phase utilizes the following hardware and software specifications:

1. Hardware

PC/Laptop	: ASUS VivoBook 14 X441MA
Processor	: Intel® Celeron® N4000 CPU @ 1.10 GHz
RAM	: 8 GB DDR4
SSD	: ADATA SU650 477 GB
Graphics Card	: Intel® UHD Graphics 600

2. Software

Operating System	: Windows 10 Pro 22H2
DBMS	: SQLite(3.40.0)
Framework	: Laravel (13.18.0)
Local Development Environment	: Laragon (v7.0.5)
Tools	: Draw.io(31.1.9), Balsamiq Cloud (2026)
Browser	: Microsoft Edge(151.0.4129.72), Google Chrome(151.0.7922.77)

D. System Testing (*Testing*)

This phase aims to ensure that the developed system aligns with the requirements and is free of errors. Testing is conducted using the Black Box Testing method for functional validation, evaluation of the K-Means Clustering method (including Elbow Method verification, distance calculation, cluster formation, centroid updates, and inertia measurement), and User Acceptance Testing (UAT) with the shop owner to assess usability and the appropriateness of the clustering results. The clustering outputs are displayed as priority recommendations for stock management..

E. Maintenance

This phase takes place after the system is operational, encompassing error corrections, adjustments to new requirements, and system performance enhancements.

2.3. Research Object and Dataset

The object of this research is the **historical sales transaction data** at Toko Kacamata Nobita from January to April 2026, comprising a total of 308 transactions across 113 types of items with inbound and outbound transaction histories. A sample of the sales transaction data is presented in Table 1.

Table 1. Sales Transaction Data

No	Date	Name	Frame	Lens
1	03-Jan-2026	AVITHYA FATIMAH	ONASIS	BLUERAY
2	03-Jan-2026	ELIANTINA	ABR	KRY MC CR
...	...	...	...	...
308	26-Apr-2026	ALHADI	CARTIER	BLUE CROMIC + SV FOTO

The transaction data continues up to 308 recorded transactions within the January to April 2026 period. From these transactions, a summary was compiled for **113 types of items** that possess inbound and outbound transaction records. This summary includes attributes such as stock, purchase price, total inbound items, and total outbound items, which serve as the foundation for the clustering process. A sample of the item dataset used is presented in Table 2.

Table 2. Item Data

No	Item Name	Stock	Purchase Price (Rp)	Total Inbound	Total Outbound
1	ABR	36	110.000	66	41
2	CAZARA	12	280.000	18	8
...	...	...	...	...	...
113	GENTLE MONSTER	6	835.000	8	3

The attributes for stock, purchase price, total inbound, and total outbound in the dataset are subsequently normalized using Min-Max Normalization. This step standardizes the attribute scales prior to the distance calculation process in the K-Means Clustering algorithm.

2.4. K-Means Clustering Calculation Method

K-Means Clustering is a non-hierarchical clustering technique that partitions data into a predetermined number of clusters based on the proximity of each data point to the center point (centroid) of its respective cluster[12]. The process begins by determining the number of clusters, selecting initial centroids, and calculating the distance from each data point to all centroids using Euclidean Distance[13]. The centroids are then updated iteratively by computing the mean value of the members within each cluster until convergence is reached[14]. The four primary equations utilized in this study are detailed below:

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

Note: X_{norm} represents the normalized attribute value; X is the original attribute value; $X_{\min}$ and $X_{\max}$ denote the minimum and maximum values of the attribute, respectively..

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

Note: $d(x, y)$ represents the Euclidean distance between data point x and *Centroid* y ; x_i and y_i denote the i -th attribute values of the data point and the centroid, respectively.

$$C_j = \frac{1}{n} \sum_{i=1}^n X_i \quad (3)$$

Note: C_j represents the centroid value of the j -th cluster; n is the number of data points in the j -th cluster; X_i denotes the i -th data point assigned to the j -th cluster.

$$Inertia = \sum_{j=1}^k \sum_{i=1}^{n_j} d(x_i, c_j)^2 \quad (4)$$

Note: Inertia represents the total sum of squared distances from all data points to their respective cluster centroids; k is the number of clusters; n_j denotes the number of data points in the j -th cluster.

The optimal number of clusters is determined using the Elbow Method, which involves running the K-Means algorithm across various K values and plotting the relationship between K and the resulting inertia. The point where the decrease in inertia slows down drastically is defined as the "elbow point," signifying the optimal number of clusters. The system was developed using the Laravel framework with a Model-View-Controller (MVC) architecture to separate application logic, presentation, and data management systematically[15]. SQLite was selected as the database backend due to its lightweight nature, making it highly suitable for the data scale of this research[16].

2.5. Data Analysis Techniques

Functional system testing is conducted using Black Box Testing to ensure that all features operate according to the requirements. The tested features encompass authentication, master data management, inbound and outbound transactions, and the clustering process. Testing for the K-Means method is executed for $K=1$ to $K=8$ to verify the Elbow Method results. These computational outcomes are then compared with manual calculations performed on a sample dataset. Finally, a User Acceptance Test (UAT) is administered to 30 respondents, consisting of the owner, staff, and users involved in the system's operations. The evaluation utilizes questionnaires with a 1–5 Likert scale to assess system usability and the alignment of clustering results with inventory management needs.

2.6. Ethical Clearance

This study involves human subjects during the interview and User Acceptance Testing phases. Oral informed consent was obtained from the owner and staff of Toko Kacamata Nobita prior to utilizing the data in this research. Furthermore, all gathered data is exclusively used for the analytical purposes of this study.

3. RESULTS AND DISCUSSION

3.1. System Implementation Results

The development resulted in a **web-based Inventory Information System** that provides features for managing items, categories, suppliers, inbound stock, outbound stock, stock takes (stock opname), sales, users, and inventory reports that can be exported to PDF and Excel formats. Additionally, the system

provides a K-Means Clustering page that displays automated stock grouping results, which update dynamically whenever changes occur in the stock data, as illustrated in Figure 3.

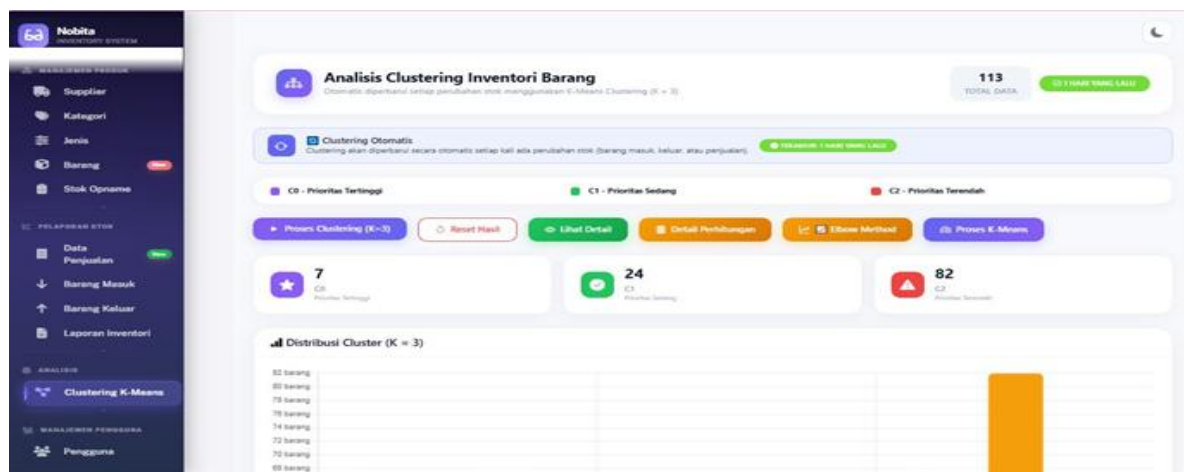


Figure 3. Stock Grouping Results

The system also features a **Clustering Result Details** page. This page displays the volume of processed data, the number of clusters, the total iterations, processing time, final centroid values, and the specific grouping results for each item, as shown in Figure 4.

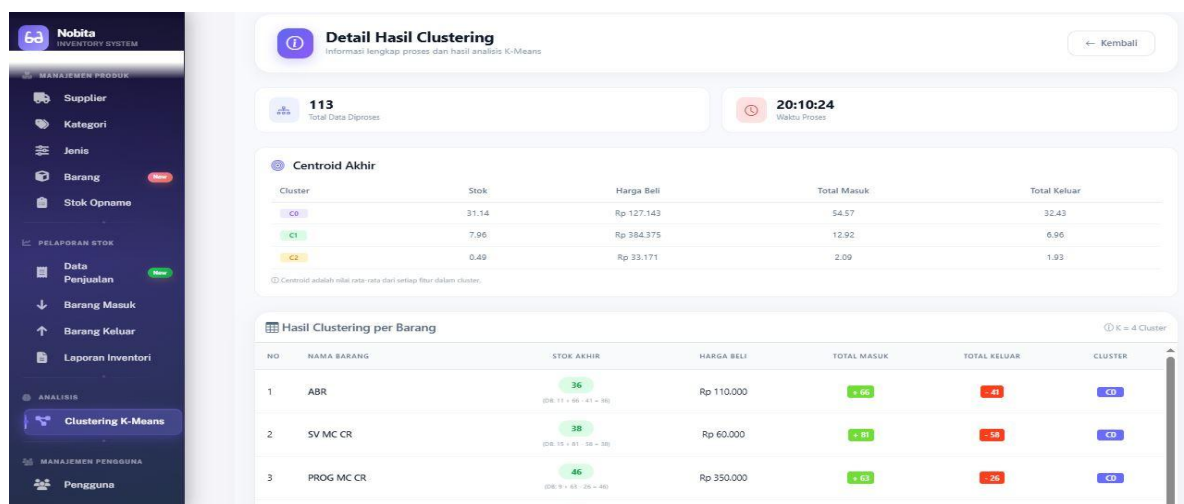


Figure 4. Clustering Result Details

3.2. K-Means Clustering Testing Results

The optimal number of clusters was determined using the Elbow Method by executing the K-Means algorithm for K=1 to K=8 on the normalized dataset of 113 items. A summary of the testing results is presented in Table 3 and visualized in Figure 5..

Table 3. Summary of Elbow Method Calculation Results

K	Total Inersia (WCSS)	Decrease	Percentage Decrease
1	13,5530	-	-
2	7,5466	6,0064	44,3%
3	3,4551	4,0915	54,2%

K	Total Inersia (WCSS)	Decrease	Percentage Decrease
4	2,4113	1,0438	30,2%
5	1,9494	0,4619	19,2%
6	1,5974	0,3520	18,1%
7	1,3736	0,2238	14,0%
8	1,2245	0,1491	10,9%

The data in Table 3 is plotted as a line chart to clarify the inertia reduction pattern across each K value, as shown in Figure 5.

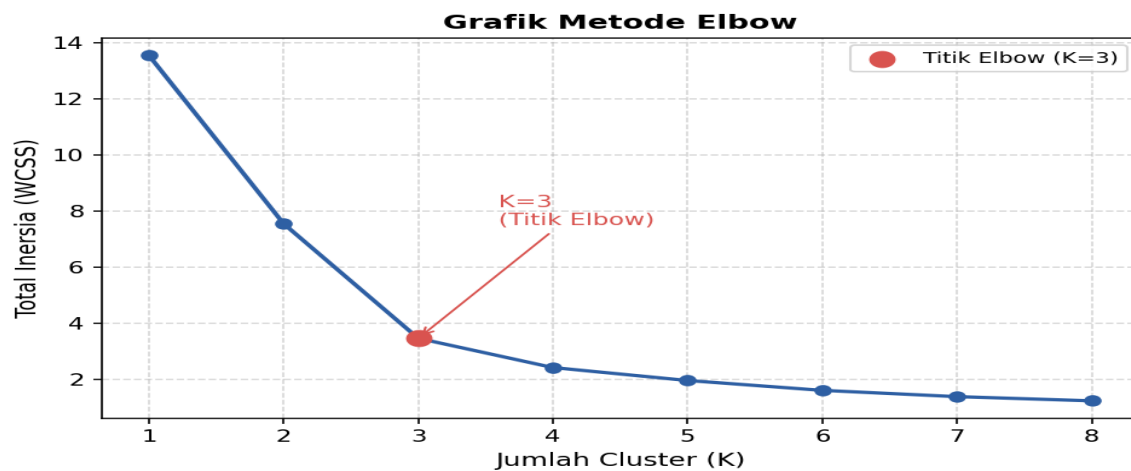


Figure 5. Elbow Method Chart

Based on Table 3 and Figure 5, the inertia decrease from K=2 to K=3 reaches 54.2%, which is significantly higher than the reduction from K=3 to K=4 (only 30.2%) and continues to shrink with subsequent increments of K. Thus, the elbow point is clearly visible at K=3, establishing it as the optimal number of clusters.

The manual calculation for K-Means Clustering used initial centroids derived from the first three data entries in the normalized dataset. The iterative process of Euclidean distance calculations and centroid updates reached convergence at the 5th iteration, yielding a final Total Inertia of 3.455093. This value is identical to the inertia value obtained in the Elbow Method test for(K=3, confirming computational consistency from start to finish. The three resulting clusters were then sorted by their average total outbound items to determine their interpretive labels, as detailed in Table 4..

Table 4. Cluster Interpretation Based on Average Total Outbound Items

Raw Cluster	Cluster Members	Total Outbound	Average	Final Classification
Cluster 0	7	227	32,43	C0 (Sangat Laris)
Cluster 1	24	167	6,96	C1 (Laris)
Cluster 2	82	158	1,93	C2 (Kurang Laris)

3.3. Black Box and User Acceptance Test Results

Black Box testing focused on the K-Means Clustering feature as the core of this research, which encompasses the automated clustering process, the clustering results display, and the detailed calculation breakdowns. The testing outcomes are presented in Table 5.

Table 5. K-Means Clustering Black Box Testing

No	Tested Feature	Test Scenario	Expected Outcome	Remarks
1	Automated Clustering Process	Adding inbound/outbound stock data (including from sales), triggering inventory data updates	The system automatically executes the clustering process and updates the grouping results	Valid
2	Clustering Results	Navigating to the clustering results page	The system displays the item grouping results into clusters C0, C1, and C2.	Valid
3	Calculation Details	Navigating to the clustering calculation details page.	The system displays the K-Means calculation steps, including normalization, distance computation, centroids, and iteration phases	Valid

The results in Table 5 demonstrate that all test scenarios for the K-Means Clustering feature operated exactly as expected with no functional errors detected. This outcome indicates that the automation of the clustering process during stock fluctuations has been correctly implemented according to the initial design.

The User Acceptance Test (UAT) involved 30 respondents, consisting of the owner, staff, and users who interact directly with the system. The evaluation utilized questionnaires based on a 1–5 Likert scale.

The evaluation yielded an average user acceptance rate of 89%, placing it in the "excellent" category. The highest score was achieved in the aspect of interface usability/clarity at 95%. Conversely, the lowest scores were observed in menu and feature accessibility, utilization of clustering results, and system stability, which each received 85%. Despite these lower scores, every evaluated aspect remained firmly within the "excellent" category.

Table 6. UAT Results from 30 Respondents

Assessment Aspect	Percentage	Category
Interface usability and clarity	95%	Excellent
Menu and feature accessibility	85%	Excellent
Appropriateness of clustering results	90%	Excellent
Utilization of clustering results	85%	Excellent
System stability	85%	Excellent
Average	89%	Excellent

Compared to previous studies implementing K-Means Clustering, this research establishes a **direct integration between the clustering outcomes and the operational inventory system**. Consequently, the grouping process runs automatically during stock adjustments without requiring manual intervention or standalone analytical workflows. The consistent alignment between the Elbow Method evaluation and manual computations—which generated identical inertia values at $K=3$, solidifies the validity of the algorithm's implementation. Furthermore, the 89% user acceptance rate indicates that the visualized clustering results are easily understood and practically applicable for the shop owner to prioritize inventory management effectively.

4 CONCLUSION

Based on the design, implementation, and testing phases conducted, it can be concluded that a web-based Inventory Information System was successfully developed using the Laravel framework and SQLite database, featuring fully integrated item, stock, transaction, and reporting management. The K-Means Clustering method was successfully deployed to group 113 types of items based on 308

transactions from January to April 2026 utilizing normalized attributes for stock, purchase price, total inbound, and total outbound. The Elbow Method determined an optimal cluster count of $K=3$, which reached convergence at the 5th iteration and produced three stock movement categories: fast-moving, medium-moving, and slow-moving. Black Box testing confirmed that all features operate according to specifications, and the User Acceptance Test achieved an 89% acceptance rate in the "excellent" category. Thus, the system is proven to help Toko Kacamata Nobita manage its inventory priorities more objectively and efficiently. Future research is advised to explore alternative clustering techniques or artificial intelligence models alongside performance evaluations to identify the most robust methodology. Additionally, expanding the historical sales dataset would allow the clustering results to better reflect long-term trends. Future work should also consider enhancing the system by integrating demand forecasting features, minimum stock notifications, and connections to external e-commerce or sales platforms.

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