



Enhancing Product Management Strategies: A Case Study of Indonesian E-Commerce Using a Data-Driven Machine Learning Approach

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Abstract

Background: In online marketplaces where thousands of products compete with similar prices and ratings, sellers struggle to decide which products deserve promotion, retention, or removal. As competition in Indonesian e-commerce intensifies, data-driven approaches are needed to manage product performance.

Objective: This study aims to formulate a product management strategy using a two-stage data-driven approach. It focuses on performance-based product segmentation and classification and identifies the key variables that show the strongest relationships with performance segments and sales outcomes.

Method: This study uses a census-type sample of 2,547 household products in the “Rumah Tangga” category on Tokopedia, collected via web scraping in April 2025. K-Means clustering segments products based on product rating, total product ratings, store rating, and total store ratings; Random Forest classifies products into the identified segments; and correlation analysis examines relationships between attributes, performance segments, and sales outcomes.

Results: The segmentation analysis produced three product performance segments: low, medium, and high. The Random Forest classifier categorized products into these segments with 99.4% accuracy. Correlation analysis indicates that product and store ratings play a central role in differentiating performance segments, while the number of product ratings is more closely associated with sales outcomes.

Conclusion: The findings support strategies such as targeted promotions for high-performing products and inventory adjustments by segment, while strengthening customer rating engagement and store reputation to improve product performance signals. This study extends the literature on data-driven product management by demonstrating how a combined segmentation-classification approach can operationalise performance-based portfolio decisions in an emerging market context.

Keywords: data-driven strategy; e-commerce; machine learning; product performance; segmentation

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1. Introduction

The growth of e-commerce in Indonesia has accelerated rapidly in recent years, making it one of the main pillars of the national digital economy. Recent studies identify e-commerce as a key driver of digital transformation, supported by rising internet penetration and widespread mobile device usage (Fashola & Kusuma, 2024; Narayan, 2025). According to the latest e-Conomy SEA 2025 report by Google, Temasek, and Bain & Company, Indonesia's digital economy is expected to reach nearly reach US\$100 billion in Gross Merchandise Value (GMV) in 2025, growing by about 14% year over year and remaining the largest in Southeast Asia. E-commerce continues to be the main contributor to this value and is projected to expand by more than 14% to around US\$71 billion in GMV in 2025. In line with this expansion, the Central Statistics Agency (Badan Pusat Statistik) (2025) reports a steady increase in the number of e-commerce business units in Indonesia, which reached about 4.4 million rupiahs in 2024, reflecting the growing number of enterprises that sell goods and services through online channels (Badan Pusat Statistik, 2025; Google, Temasek, & Bain & Company, 2025).

In a market full of similar products, understanding how each product performs from the consumer's perspective becomes critical. Product ratings have emerged as a central indicator in building trust and perceived value. Empirical studies show that high ratings significantly increase consumer trust and, together with reviews, can explain a substantial share of the variance in purchasing decisions (Chen et al., 2022; Kaimann et al., 2023; Magnusson, 2022; Rachmiani et al., 2024). From a consumer behaviour perspective, ratings and reviews act as cues that help consumers evaluate perceived quality and risk when information is limited, thereby influencing brand attitudes and choice. In line with information asymmetry and signalling theory, online ratings can also be viewed as signals that reduce uncertainty about product quality in digital markets where sellers typically know more than buyers (Akerlof, 1970; Mavlanova et al., 2012; Senecal & Nantel, 2004). Consequently, not only do ratings function as markers of quality, but also as strategic instruments that shape market perceptions, direct consumer preferences, and influence sales performance on e-commerce platforms (Populix, 2023).

In practice, marketing management explains that market segmentation is a crucial first step in understanding consumer preferences more clearly. Segmentation is the process of dividing a market into groups with distinct needs, characteristics, or behaviours that can be effectively served through a tailored marketing mix (Kotler & Keller, 2021). This approach later evolved into product segmentation, which involves businesses grouping their products into distinct categories based on features, price, or utility to address diverse market preferences (Ferrell et al., 2023). Through segmentations, businesses can identify high- and low-performing product groups, which then form the basis for determining promotional priorities, visibility strategies, and inventory management.

However, segmentation alone is not enough to keep pace with an ever-changing market, especially on e-commerce platforms that continually introduce new products. In this context, classification plays a crucial role in automatically mapping new products into relevant segments. Several studies have demonstrated the practical benefits of combining segmentation and classification techniques to enhance decision-making. Wong et al. (2024) applied K-Means and Hierarchical Clustering within an RFM-based strategy to identify customer segments, while Yoloan et al. (2023) used K-Means to analyse transaction patterns and seasonal trends, enabling better promotional planning. Kızgın and Alp (2024) emphasise that classification improves managerial efficiency by enabling faster, data-driven decisions. In the context of product analysis, Ridwan et al. (2024) and Tabianan et al. (2022) utilised K-Means to segment products based on consumer behaviour and numerical attributes.

In contrast, Kumari et al. (2024) and Li (2022) employed Random Forest and XGBoost to classify and predict product performance. A similar two-stage framework was introduced by Li (2025), who combined K-means clustering with random forests to predict customer churn. These studies demonstrate that, despite their technical approaches, segmentation and classification offer direct benefits in a managerial context, particularly by improving the accuracy of marketing strategies and enabling efficient product management amid dynamic digital competition.

Despite this progress, several gaps remain. First, most previous studies focus on optimising predictive accuracy without explicitly linking their results to managerial decision-making in product portfolio management. Second, the combination of clustering and classification methods has mainly

been used for customer segmentation or churn prediction (Kumari et al., 2024; Li, 2025), while applications to rating-based product performance segmentation remain limited, particularly in the Indonesian digital market. A number of studies such as from Ridwan et al. (2024) and Tabianan et al. (2022) have used K-Means to group products or consumers based on numeric attributes. However, few have developed classification systems that automatically assign products to the identified performance segments and translate these outputs into concrete product management strategies.

This study addresses these gaps in the context of Tokopedia's household product category. From a practical viewpoint, sellers on large platforms such as Tokopedia a systematic guidance in distinguishing which products deserve priority in promotion, visibility, and inventory allocation when many items share similar prices and ratings. From a research viewpoint, there is a need to connect product-level segmentation and predictive classification models with performance-based product management strategies in Indonesian e-commerce. To respond to these needs, this study has two main objectives: (1) to apply a combined clustering and classification approach to group and classify product performance based on rating and store reputation data in the Indonesian e-commerce context, and (2) to link the outputs of these machine learning models to strategic recommendations that can be directly applied in business practice.

To achieve these objectives, this study proposes a two-stage, data-driven approach to product management. First, K-Means clustering is used to segment household products based on key numerical attributes, namely product rating, total number of ratings, store rating, and total store ratings. Second, a Random Forest classification model is developed to automatically classify products into the identified performance segments based on their attributes. In addition, a correlation analysis of numerical variables is conducted to identify the factors most strongly associated with product performance. Together, these steps aim to help businesses differentiate between higher- and lower-performing products and to support more informed decisions on product visibility, promotion, and inventory in the Indonesian e-commerce market.

2. Literature Review

2.1. Data-Driven Product Management in an E-Commerce Context

Today's online market is changing rapidly, and customer expectations are increasing. This situation necessitates product management with a data-driven approach. With data analytics, e-commerce businesses can better understand consumer preferences, improve product features, and strategise to align products with real-time market trends (Jakkula, 2024). Social media, product usage, and customer feedback are among the information sources that can be analysed and processed to enable quicker, more precise decisions (Grigoryan et al., 2023). Employing a data-driven strategy streamlines product classification and helps businesses identify effective tools and platforms for managing the product life cycle (Fichtler et al., 2024). In turn, data-driven product management enables firms to meet customer demand better, strengthen their market position, and increase productivity in highly competitive online marketplaces.

In this study, the term “e-commerce” refers specifically to marketplace-based online retail in Indonesia, with Tokopedia serving as the focal platform case in the empirical analysis.

From a broader theoretical perspective, this study is grounded in the Resource-Based View (RBV), which argues that firms achieve sustained competitive advantage when they develop resources and capabilities that are valuable, rare, difficult to imitate, and non-substitutable (Barney, 1991). In the context of e-commerce, product-level data such as ratings, review volumes, and store reputation, together with machine-learning-based analytics, can be viewed as strategic informational resources and analytical capabilities. Recent RBV-based studies conceptualise big data and analytics capabilities as strategic resources that enhance firm and market performance in digital environments (Aziz et al., 2023; Huang et al., 2022; Olabode et al., 2022; Vitari & Raguseo, 2020). In line with this view, the present study treats the proposed segmentation–classification model as a data-driven capability that supports superior product portfolio decisions on e-commerce platforms such as Tokopedia.

2.2. Product Segmentation and K-Means Clustering

Product segmentation is a business's attempt to organise its products within defined boundaries, such as price, utility, or features. As with most segmentation strategies, the objective of product segmentation is to match offerings with customer desires (Ferrell et al., 2023). The primary advantage of product segmentation is that it enables the business to identify underperforming and high-performing products. One method of segmentation in data analysis is K-Means Clustering, which falls under the category of unsupervised learning. It partitions data into k clusters based on their centroids, a process that involves calculating the distance of each data point to each cluster's centroid. Thus, all products will be categorised into several groups or clusters having common or similar features. The K-means algorithm attempts to limit the difference in each of the clusters, a process referred to as the Within-Cluster Sum of Squares (WCSS), with the subsequent formula:

$$E = \sum_{i=1}^k \sum_{x \in C_i} \|x - \mu_i\|^2$$

Where x is the data in cluster C_i , and μ_i is the i -th cluster centre. A number of e-commerce studies have used K-Means Clustering. For example, Ridwan et al. (2024) used K-means clustering to group products based on ratings and reviews. By using patterns from available data, businesses can classify high-performing and low-performing products using a data-driven segmentation approach.

2.3. Product Classification and Random Forest

Product classification is one of the steps or tools in product management. The goal is to identify patterns in past data so new products can be assigned to predetermined performance groups. In the context of e-commerce, classification helps business actors quickly select from thousands of products without having to check each one. Random Forest is one algorithmic technique that can be used. Random Forest is an ensemble learning algorithm that works by inviting many trees to make decisions together. This method creates multiple decision trees, each trained on randomly selected data. Each tree is then given an opinion or prediction. The final result is determined by a majority vote from all the trees. This algorithm, according to Géron (2019), usually uses the Gini Index to decide branch separation when creating a decision tree, with the following formula:

$$\text{Gini}(D) = 1 - \sum_{i=1}^n p_i^2$$

Where p_i denotes the proportion of the i -th class within a given data subset D . Research by Kumari et al. (2024) shows that Random Forest can accurately classify customers, especially when used after a segmentation process like K-Means. Combining segmentation with Random Forests can predict customer churn on e-commerce platforms (Li, 2022).

2.4. Correlation Matrix for Product Strategy Decisions

Analysing the correlation matrix can enhance product management within a business. Through this analysis, companies can appreciate and understand the relationships among various numerical variables that affect product performance. A typical case in e-Commerce involves a number of factors, such as the price of a product, its reviews and ratings, among others, and their strategic impacts on sales and, overall, on business perception. As noted by Shah (2023), in a highly crowded and dynamic environment, correlation analysis is a powerful tool for identifying the most important factors and the underlying, interconnected relationships that can shape consumer behaviour. This kind of information is very important in business, since it can justify the most important variable to consider when designing advertisements, overseeing product quality, or even managing product stock. Furthermore, Jakkula (2024) emphasised that integrating correlation matrix analysis into product management systems promotes evidence-based decision-making, enabling businesses to allocate resources better, streamline operations, and optimise product development initiatives. Another study by Grigoryan et al. (2023) showed that understanding the correlations among product attributes is a crucial first step toward

creating more effective segmentation and classification strategies, as these relationships significantly influence data structure and predictive model results.

2.5. *Novelty and Position of This Research*

Previous studies using K-Means and Random Forest in the e-commerce context have generally focused on customer segmentation or churn prediction, rather than product performance segmentation (Kumari et al., 2024; Li, 2025). Furthermore, most of these studies emphasize model accuracy and technical performance without explicitly linking the results to strategic implications for product portfolio management.

Against this backdrop, the present study contributes in two main ways. First, it applies a combined clustering–classification approach to group and classify product performance based on rating and store reputation data at the product level, in the underexplored context of Indonesian e-commerce and Tokopedia’s household product category. Second, it explicitly connects the machine-learning outputs to a set of managerial strategies for product visibility, promotion, and inventory decisions, thereby positioning the model as a practical decision-support tool for e-commerce product management rather than a purely predictive exercise.

3. **Method**

3.1. *Sample*

This study adopts a quantitative explanatory case study design using secondary product-level data from an Indonesian e-commerce platform. The sample consists of 2,547 household products in the “Rumah Tangga” category on Tokopedia. This category was selected based on the high consumer preference for this product type on Tokopedia. The dataset is cross-sectional and was collected via web scraping in April 2025 using a census-type approach, in which all products in the selected category that were active during the data collection period and had complete information on the required attributes were included. The main attributes in the dataset include product price, product rating, total number of ratings, total units sold, store rating, and total store ratings. Each row of data represents a product that was available and sold on Tokopedia at the time of data collection. Examples of the dataset are shown in Tables 1a and 1b below.

Table 1a. Product Dataset Example (Part 1)

Product Name	Product Price (IDR)	Product Rating	Total Product Ratings	Total Units Sold
Hafele Mainz Slim Cooker Hood – Penghisap Asap Dapur...	1,785,000	5.0	7	17
SN07 Cobek/Coet Gagang Aluminium Garut Diameter 19cm Anti Karat.	60,000	4.9	9	22
KOMPOR PANGANGAN SOSIS/BAKARAN SERBAGUNA OMICKO 3 Tungku - PLUS SELANG...	711,000	5.0	27	60
vesper espresso shot square cup 90ml borosilcate glass / gelas takar ukur kaca kopi susu aesthetic...	28,000	4.8	25	100
Sodet Irus Jumbo Stainless Gagang Kayu Merk Komodo 38cm - Komodo Irus.....	39,900	4.9	116	250

Table 1b. Product Dataset Example (Part 2)

Store Name	Store Rating	Total Store Ratings	City	Category
@RUMAHKU	4.9	73,000	Kota Administrasi Jakarta Barat	Cook ware
Fany onderdil	5.0	26	Kab. Bandung	Cook ware
TOKO JAWA ELEKTRIK	4.8	46,100	Kota Administrasi Jakarta Timur	Cook ware
Vesperindo_NEW	4.9	208,500	Kota Administrasi Jakarta Barat	Cook ware
WolloStore	4.9	40,600	Jakarta Barat	Cook ware

3.2. *Instrument(s)*

This study did not employ traditional survey instruments, as all analyses were conducted using secondary product-level data. Instead, the primary research instrument was a Python-based computational environment for data preprocessing, modelling, and evaluation. The main libraries included pandas for data processing, scikit-learn for machine learning, and matplotlib and seaborn for data visualisation.

Within this environment, the K-Means clustering algorithm was used in the segmentation stage to group products based on numerical features such as product rating, store rating, total product ratings, and total store ratings, while the Random Forest classifier was used in the classification stage to assign products to the pre-defined performance segments. The technical details of the preprocessing steps and model evaluation procedures are described in the subsequent subsection on data analysis.

Table 2. Operational Variables

Attribute / Variable	Brief Description	Initial Data Type	Transformed Data Type
Product Rating	User-assigned rating for the product (scale 1–5)	Real (float)	Real (float)
Total Product Ratings	Total number of ratings received by the product	Integer	Integer
Store Rating	Average rating received by the store	Real (float)	Real (float)
Total Store Ratings	Total number of ratings received by the store	Integer	Integer
Product Price	Selling price of the product in Indonesian Rupiah	Integer	Integer
Product Name	Product name as displayed on Tokopedia	Text (Polynomial)	Encoded (Integer)
Store Location (City)	Seller's location based on city name	Text (Polynomial)	Encoded (Integer)
Product Category	Type of product based on Tokopedia's classification	Text (Polynomial)	Encoded (Integer)
Total Units Sold	Total number of product units sold on the platform	Integer	Integer

3.3. Data collection procedures

The data in this study were obtained through web scraping techniques from the Tokopedia platform using the Webscraper.io extension integrated with Google Chrome. Data collection took place in April 2025 and focused on the household appliances category. During data collection, only products with a rating of approximately 4.0 or higher could be retrieved. As a result, the dataset primarily consists of products that are already well-rated on the platform. While this limitation stems from the scraping tool's access constraints, it also aligns with the research objective of analysing products with consumer-acceptable performance.

The initial dataset contained 2,547 product entries with information such as product name, product price, product rating, total number of product ratings, total units sold, store name, store rating, total store ratings, city, and product category. All data were compiled into CSV format for further processing using Python.

The main stages in data processing are as follows:

1. Data cleaning: Removing duplicate records and entries with missing or inconsistent values to ensure that only valid and complete observations are retained in the analysis.
2. Numeric variable selection: Selecting the numerical variables relevant to product performance, such as product rating, total product ratings, store rating, and total store ratings, which serve as inputs for the segmentation and subsequent analyses.

3. Normalisation: Standardising the selected numerical features using Z-score normalisation so that variables with different original scales can be compared and processed on an equal scale.
4. Categorical variable encoding: Converting categorical variables such as city and product category into numerical form using one-hot encoding to make them compatible with the machine learning algorithms.
5. Data splitting: Dividing the dataset into training data (80%) and test data (20%) for the Random Forest classification stage, so that the model performance can be evaluated on previously unseen data.

These preprocessing stages ensure the data is ready for optimal processing in the machine-learning-based product clustering and classification. Figure 1 below illustrates the overall research stages adapted from the CRISP-DM (Cross-Industry Standard Process for Data Mining) approach.

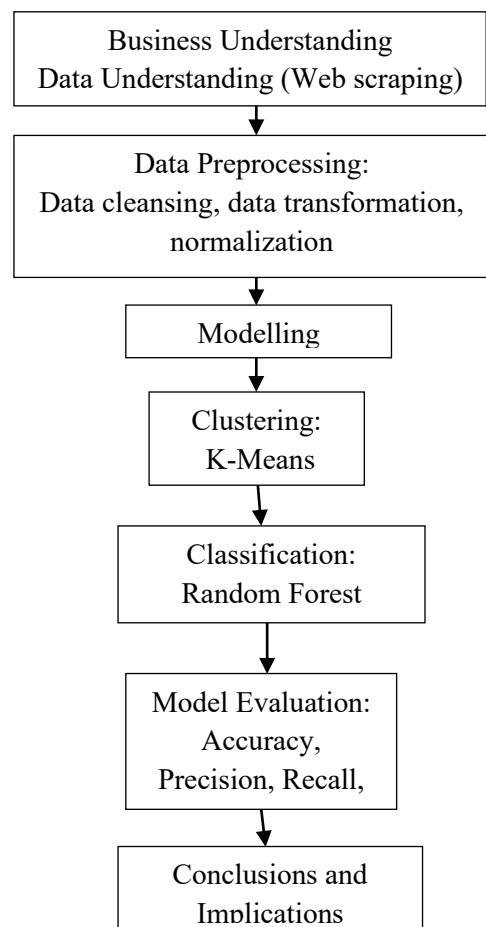


Figure 1. Data Analysis Process Flow (Adapted from CRISP-DM Framework)

The process begins with understanding the business context and collecting data through web scraping, followed by preprocessing, product segmentation using the K-Means algorithm, new product classification using Random Forest, and finally, model performance evaluation and strategic implications formulation.

3.4. Data analysis

The data analysis in this study followed three main steps: (1) data preprocessing, (2) product performance segmentation using K-Means clustering, and (3) segment classification for new products using the Random Forest algorithm, followed by a correlation analysis to understand the relationships among the key variables better.

In the preprocessing stage, numerical variables were standardised using Z-score normalisation to ensure a comparable scale across attributes. Categorical variables, particularly product and store names, were converted to numerical form using one-hot encoding. The final dataset was then split into a training set (80%) and a test set (20%) for model development and evaluation.

In the segmentation stage, K-Means clustering was applied to four normalized numerical variables: product rating, total product ratings, store rating, and total store ratings. The algorithm was used to group products into performance segments based on similarities in these attributes. An exploratory assessment of the data distribution and the managerial purpose of performance grouping led to the selection of three clusters, interpreted as low-, medium-, and high-performance product segments.

In the classification stage, the K-Means cluster labels were used as target classes for a Random Forest classifier. The model predicts performance segments using the selected product- and store-level attributes in the dataset: product name, product price, product rating, total product ratings, total units sold, store name, store rating, and total store ratings. Model performance was evaluated on the test set using accuracy, precision, recall, and F1-score, complemented by a confusion matrix and a classification report to assess the model's ability to assign products to the three performance segments correctly.

Finally, a correlation analysis was conducted on the main numerical variables and the assigned performance segments to identify patterns in how product- and store-level indicators are associated with product performance. The detailed empirical results of these analyses are presented in the Results and Discussion section.

4. Results

4.1. Product Segmentation Results (K-Means)

The K-Means clustering algorithm was used to segment products based on four normalized numerical attributes: product rating, total product ratings, store rating, and total store ratings. This study then produced three cluster groups. Table 3 presents the distribution of product counts across clusters based on the segmentation results.

Table 3. Product Distribution Based on Clustered Segments

Cluster Labels	Performance Segment	Total Products
0	Low	592
1	High	1,820
2	Medium	128

4.2. Characteristics of Each Segment

After the clustering process, an analysis was carried out to identify the characteristics of each segment based on the average values of the numerical variables used in the model. Table 4 presents the average results of each variable: product rating, store rating, total product ratings, and total store ratings for each clustered segment.

Table 4. Numeric Attributes in Each Clustering Result Segment
(Tokopedia “Rumah Tangga” products, April 2025)

cluster_rating	Product Rating	Store Rating	Total Product Ratings	Total Store Ratings
0	4.712162	4.719257	163.996622	21,755.162162
1	4.882031	4.851562	1,740.203125	318,792.968750
2	4.943671	4.890110	147.615934	26,124.944505

The analytical findings indicate that Segment 1, categorised as high-performing, has the highest average for both product and store rating counts. This suggests that products in this group tend to receive

more frequent ratings and are associated with stores that have stronger reputational standing. Conversely, segments 0 (low) and segment 2 (medium) have relatively fewer ratings, even though the average product ratings for both are quite high. Segment 2 shows the highest average ratings for product and store; however, the total number of ratings received remains comparatively lower than in the other segments.

The considerably higher volume of ratings observed in Segment 1 may be attributed to the inherently uneven distribution of product ratings on e-commerce platforms. Prior studies have shown that a limited subset of products tends to accumulate the majority of user attention and ratings, while the vast majority receive minimal engagement. This pattern reflects a long-tail distribution, wherein a small number of products dominate user interactions (Rezvani & Rezvani, 2020). Furthermore, popular products tend to garner even higher ratings over time. There is a phenomenon known as the "rich-get-richer effect," where products with a high number of ratings continue to receive new ratings because buyers perceive them as more relevant and trustworthy (Solimine & Isaac, 2023). Products in this segment are also typically from well-known sellers or popular categories, often appearing frequently in search results or frequently purchased, resulting in more people interacting with them, viewing, purchasing, and rating or reviewing them. Because of this high level of interaction, these products are grouped into a single high-attention segment in our results, forming a cluster that stands out from the others (Dash et al., 2021; Klimashevskaya et al., 2024; Nakano, 2023).

4.3. Classification Results (Random Forest)

After the products were divided into three performance categories using K-Means, the Random Forest model was trained on 80% of the data and evaluated on the remaining 20% using accuracy, precision, recall, and F1-score in Table 5. This was done to evaluate performance on held-out data / to assess classification accuracy.

Table 5. Random Forest Model Evaluation Results

Evaluation Metrics	Value
Accuracy	0.994
Precision (Macro Avg)	0.995
Recall (Macro Avg)	0.962
F1-score	0.977

The model achieved 99.4% accuracy in correctly classifying products. High precision and F1-score values indicate good and consistent model performance across all segments.

In addition, Table 6 below presents a confusion matrix showing the number of correct and incorrect predictions by segment.

Table 6. Confusion Matrix of Random Forest Model

	Predicted: Low	Predicted: Medium	Predicted: High
Actual: Low	118	0	0
Actual: Medium	1	23	2
Actual: High	0	0	364

The confusion matrix in Table 6 summarises the model's classification performance across the three product performance segments. The diagonal cells represent correct predictions, while the off-diagonal cells represent misclassifications.

The model correctly classified all observations in the low and high segments, with 118 and 364 products, respectively, assigned to the correct class. For the medium segment, 23 out of 26 observations were correctly classified, while the remaining 3 were misclassified into the low (1) and high (2) segments.

These results indicate that the model has very high accuracy in recognising patterns in segments with large data volumes (low and high), while still maintaining good performance in the smaller segment (medium), despite a small number of misclassifications.

4.4. Correlation Analysis Between Variables

Correlation analysis was performed to evaluate the linear relationships among numerical variables used in segmentation and classification modelling. Correlation was calculated using the Pearson correlation coefficient, which indicates the strength and direction of the relationship between two variables, ranging from -1 to 1. The correlation between variables is visualised in the following heatmap.

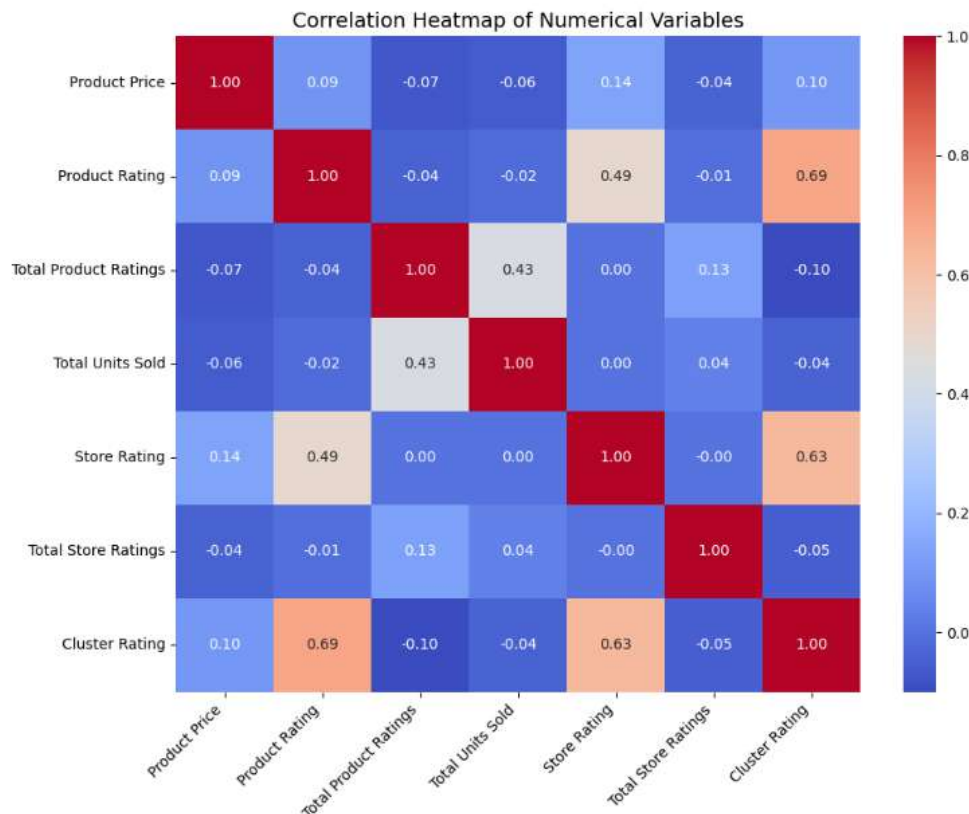


Figure 2. Correlation Heatmap of Numerical Variables

Based on the heatmap, several notable relationships are evident among the variables. The strongest association with Total Units Sold is Total Product Ratings ($r = 0.43$), suggesting that products with more accumulated ratings tend to achieve higher sales volumes. In addition, Store Rating shows moderate associations with Product Rating ($r = 0.49$) and Cluster Rating ($r = 0.63$), indicating that store reputation is closely aligned with how products are positioned across the product performance segments.

Meanwhile, Product Price and Total Store Ratings show weak or near-zero correlations with Total Units Sold, indicating that these variables do not have a clear linear relationship with sales volume in this dataset. Similarly, Total Store Ratings shows a near-zero correlation with Cluster Rating ($r = -0.05$), suggesting that the volume of store ratings is not strongly associated with performance segments relative to rating scores.

These findings offer two practical priorities for sellers: (1) Sellers should encourage buyers to leave ratings to increase Total Product Ratings, as this engagement signal is the variable most closely associated with Total Units Sold; (2) Sellers should maintain store reputation to sustain a high Store Rating, which is strongly associated with Cluster Rating and therefore closely related to product performance segment positioning. Importantly, these insights are based on correlations and should be interpreted as descriptive associations rather than causal effects.

4.5. Summary of Key Findings

The results of this study indicate that a combined clustering-classification framework can serve as a data-driven tool for managing product performance on e-commerce platforms. K-Means clustering grouped household products into three performance segments (low, medium, and high) based on product and store rating information, while the Random Forest model achieved very high accuracy (99.4%) with consistently strong precision, recall, and F1-score across all segments.

The correlation matrix indicates that the performance segments obtained from the clustering process are mainly associated with product and store ratings. At the same time, sales outcomes are more closely related to the number of ratings a product has accumulated. In other words, products and stores with better ratings tend to fall into higher-performing segments, and products that receive more ratings tend to record higher sales than comparable items in the same category. This pattern underscores the importance of maintaining strong product and store reputations and actively encouraging customers to leave ratings and reviews, as these elements are linked to both a product's position in the performance segments and its realized sales.

These findings suggest that clustering and classification can be used to allocate promotions more efficiently, manage inventory by segment, prioritise high-performing products, and design interventions for low-performing items. Based on this summary of key findings, the next subsection presents a set of managerial strategies that translate the model outputs into concrete product management actions.

5. Discussion

This study set out to understand how product performance in Indonesian e-commerce can be segmented, predicted, and explained using product- and store-level information. First, the results show that household products on Tokopedia can be grouped into three distinct performance segments (low, medium, and high) using K-Means clustering. These segments reflect how ratings and reputation are distributed in the marketplace. The high-performing segment is characterised by higher average product and store ratings, as well as a much larger number of product ratings, indicating that products in this group attract more evaluations and are linked to stores with stronger reputational standing. In contrast, products in the low- and medium-performing segments receive fewer ratings, even though their average ratings are relatively high. This pattern is consistent with the tendency of online attention and feedback to concentrate on a limited subset of popular items in digital markets.

Second, the study examined whether these performance segments can be predicted reliably for new products using a classification model. The Random Forest classifier achieved an accuracy of 99.4% in assigning products to the three segments based on their attributes, indicating that the segmentation structure is not only descriptively meaningful but also highly reliable. This supports previous findings that Random Forest can effectively classify large volumes of product data based on their characteristics (Kumari et al., 2024; L. Li, 2022) and extends them by embedding the classifier into a two-stage segmentation–classification pipeline. In practical terms, this allows managers to infer the likely performance segment of newly listed products even when full sales histories are not yet available.

Third, the correlation analysis reinforces that engagement signals and store reputation matter in different ways. Sales outcomes are most closely linked to the volume of customer feedback (Total Product Ratings). At the same time, segment positioning (Cluster Rating) is more closely aligned with rating-based quality signals (Product Rating and Store Rating), as expected, given that these indicators were used to form the segments. These findings align with those of Rachmiani et al. (2024) and Chen et al. (2022), who show that store image and seller reputation, alongside product attributes, play an important role in building customer trust and driving purchase decisions in e-commerce.

From a theoretical perspective, the findings contribute to the literature on data-driven product management and strategic decision-making in e-commerce. Grounded in the Resource-Based View, the results illustrate how product-level information resources (such as ratings and review volumes) and machine-learning-based analytics can be combined into a data-driven capability that supports performance-based product portfolio decisions. The segmentation–classification model provides a concrete example of how routinely available marketplace data can be transformed into strategic insights

for configuring and managing product assortments in a highly competitive digital environment, particularly in an emerging market context such as Indonesian e-commerce.

From a managerial perspective, several implications emerge. Because customer ratings are strongly associated with product performance, businesses need to actively encourage legitimate rating and review behaviour and maintain service quality that sustains high store ratings. Store reputation should be treated as an integral part of product management strategies, as store-level ratings help shape performance segments. In addition, the model's performance segments can serve as a basis for decisions on stock allocation, promotional priorities, and product placement on the platform, ensuring that high-performing products receive greater visibility and inventory support. In contrast, low-performing products are reviewed for repositioning or removal.

As a follow-up to these findings, the following section presents a table of managerial strategies based on the analysis results, which can serve as a reference for formulating and implementing business-level decisions.

Table 7. Summary of Strategy Recommendations from Findings

Strategy Formulation	Strategy Plan	Strategy Implementation	Person In Charge	Monitoring & Evaluation Plan	Reference
Increase the number of Total Product Ratings	Encourage consumers to provide ratings after purchase	Send automatic reminders via email after the transaction is completed	Marketing and Customer Experience Team	Weekly monitoring of the growth in the number of ratings per product.	Rachmiani et al. (2024); Kaimann et al. (2023)
Maximizing promotions for high-performance products	Direct paid promotions to products that have proven to be superior (products in the high segments)	Use the "TopAds" feature, special discounts, and app notification campaigns for products in high segments.	Marketing and Product Team	Evaluate ad impressions, click-through rates, and sales conversions	Li (2022)
Ensuring stock availability of products in the high segments	Adjust stock allocation based on performance segmentation results	Prioritize restocks for products in the high-performance segment.	Operations & Logistics Team	Stock monitoring and product out-of-stock frequency reports	Kumari et al. (2024); Li (2022)
Increase product competitiveness in low segments	Offering incentives, or discounts for products with low performance	Implement discounts, bundling, or flash sale programs periodically	Marketing & Sales Team	Track sales changes before and after implementation	Magnusson (2022); Kızgın & Alp (2024)

6. Conclusions

The empirical results of this study confirm that a data-driven approach can effectively support product management decisions on e-commerce platforms. Using the K-Means algorithm, household products on Tokopedia were grouped into three distinct performance categories (low, medium, and high) based on key numeric attributes. The Random Forest model then mapped products to these segments with very high accuracy (99.4%), indicating that performance segments can be reliably predicted from product- and store-level information. The correlation analysis further shows that product performance segments are mainly driven by Product Rating and Store Rating, while sales outcomes are most closely associated with the volume of Total Product Ratings.

These confirmed findings provide a basis for more targeted managerial strategies, such as prioritising promotions for high-performing products, adjusting stock levels based on segment performance, and offering price incentives or repositioning options for low-performing products. Overall, the model

developed in this study can serve as a practical tool to support more efficient, measurable, and evidence-based decision-making in e-commerce in Indonesia.

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Enhancing Product Management Strategies: A Case Study of Indonesian E-Commerce Using a Data-Driven Machine Learning Approach

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ABSTRACT	HOW TO CITE	METRICS	LICENSE
Background: In online marketplaces where thousands of products compete with similar prices and ratings, sellers struggle to decide which products deserve promotion, retention, or removal. As competition in Indonesian e-commerce intensifies, data-driven approaches are needed to manage product performance. Objective: This study aims to formulate a product management strategy using a two-stage data-driven approach. It focuses on performance-based product segmentation and classification and identifies the key variables that show the strongest relationships with performance segments and sales outcomes. Method: This study uses a census-type sample of 2,547 household products in the “Rumah Tangga” category on Tokopedia, collected via web scraping in April 2025. K-Means clustering segments products based on product rating, total product ratings, store rating, and total store ratings; Random Forest classifies products into the identified segments; and correlation analysis examines relationships between attributes, performance segments, and sales outcomes. Results: The segmentation analysis produced three product performance segments: low, medium, and high. The Random Forest classifier categorized products into these segments with 99.4% accuracy. Correlation analysis indicates that product and store ratings play a central role in differentiating performance segments, while the number of product ratings is more closely associated with sales outcomes. Conclusion: The findings support strategies such as targeted promotions for high-performing products and inventory adjustments by segment, while strengthening customer rating engagement and store reputation to improve product performance signals. This study extends the literature on data-driven product management by demonstrating how a combined segmentation-classification approach can operationalise performance-based portfolio decisions in an emerging market context.			



Vol. 10 No. 1 (2026): MARCH 2026



Published: 2026-03-31

Articles

Earnings Quality and Financial Performance in State-Owned and Private Firms: A Comparative Analysis

Indra Lukmana Putra , Mochammmad Junus , Nurefa Maulana

01-16

Abstract : 162

PDF : 435 XML : 39

PDF

XML

DOI : 10.20473/tijab.v10.i1.2026.60772

Working Capital Management Practices among SMEs Owners-Managers: A Qualitative Inquiry

Imelda Jeremiah Mville Mville , Dr. Mushumbusi Kato , Dr. Gabriel Vitus Komba

17-33

Abstract : 123

PDF : 280 XML : 51

PDF

XML

DOI : 10.20473/tijab.v10.i1.2026.71825

Enhancing Product Management Strategies: A Case Study of Indonesian E-Commerce Using a Data-Driven Machine Learning Approach

Rari Fitri , Samidi

34-49

Abstract : 156

PDF : 287 XML : 58

PDF

XML

DOI : 10.20473/tijab.v10.i1.2026.77241

Determinants of Economic Growth in Indonesia: Evidence from an ARDL Bounds Test

Mochammad Nurul , Shemelis Kebede Hundie 50-69 Abstract : 117 PDF : 248 XML : 29 PDF XML DOI : 10.20473/tijab.v10.i1.2026.72689**Loyalty Retention Strategy Through After-Sales Service at Honda Car Dealers in Pekanbaru City****Trisningkasih Fitriastuti , Zulkarnain , Raden Lestari Ganarsih** 70-82 Abstract : 109 PDF : 298 XML : 45 PDF XML DOI : 10.20473/tijab.v10.i1.2026.73640**Artificial Intelligence in Service Quality Improvement: A Bibliometric Analysis****Nurkholish Majid , Ahmad Khumaeni , Hewa Majeed Zangana** 83-95 Abstract : 79 PDF : 222 XML : 30 PDF XML DOI : 10.20473/tijab.v10.i1.2026.49186**Strategy to Increase Customer Loyalty Through A Multisensory Approach at A Five-Star Hotel in Surabaya****Trinindya Eksact Daruni , Jiwangga Hadi Nata , Dian Yulie Reindrawati , Mohammad Nurul Huda , Nur Emma Suriani** 96-116 Abstract : 64 PDF : 274 PDF DOI : 10.20473/tijab.v10.i1.2026.70812**Assessing the Efficacy of the Taxation System in Tanzania: Perspectives of Small and Medium Enterprises (SMEs)****Shafii Mshata , Nsubili Isaga** 117-129 Abstract : 83 PDF : 791 XML : 21 PDF XML DOI : 10.20473/tijab.v10.i1.2026.71798**Digital Green Human Resource Management and Organisational Sustainability****Muhammad Syahrudin** 130-142 Abstract : 113 PDF : 250 XML : 53 PDF XML DOI : 10.20473/tijab.v10.i1.2026.84654

From Entrepreneurs to Startups: Rethinking Pivot Decisions through a Systematic Literature Review

 Lydia Apriliani , Muhammad Amirulafiq Juhari

 143-159

 Abstract : 103

 PDF : 261 XML : 79

 PDF

 XML

 DOI : 10.20473/tijab.v10.i1.2026.76951

Front Matter

Front Matter Vol. 10 No. 1, 2026

 Abstract : 30

 PDF : 70

 PDF

 DOI : 10.20473/tijab.v10.i1.2026.89504

Back Matter

Back Matter Vol. 10 No. 1, 2026

 Abstract : 24

 PDF : 63

 PDF

 DOI : 10.20473/tijab.v10.i1.2026.89487

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12	3457756657130123	LUHUR BAYUAJI	Ilmu Komputer (S2)
13	1654747648130072	MARDI HARDJIAN TO	Ilmu Komputer (S2)
14	9248752653130093	MOHAMMAD SYAFRULLAH	Ilmu Komputer (S2)
15	6235757658230143	RUSDAH	Ilmu Komputer (S2)
16	3444749650130102	SAMIDI	Ilmu Komputer (S2)
17	0157741642130083	SETYAWAN WIDYARTO	Ilmu Komputer (S2)
18	6356750651130093	ABDUL MUIS SOBRI	Teknik Informatika (S1)
19	5934758659137112	ACHMAD ADITYA ASHADUL USHUD	Teknik Informatika (S1)
20	4437767668130323	ACHMAD ARDIANSYAH	Teknik Informatika (S1)
21	4652761662130272	AGUNG SAPUTRA	Teknik Informatika (S1)
22	2636769670130302	AHMAD PUDOLI	Teknik Informatika (S1)
23	1646766667130292	ANGGA KUSUMA NUGRAHA	Teknik Informatika (S1)
24	4535772673130233	ANWAR RIFA'I	Teknik Informatika (S1)
25	2533753654130132	ARSANTO NARENDRO	Teknik Informatika (S1)
26	3733759660130242	BASUKI HARI PRASETYO	Teknik Informatika (S1)
27	2243767668130313	DOLLY VIRGIAN SHAKA YUDHA SAKTI	Teknik Informatika (S1)
28	9560763664230232	DWI PUSPITA ANGGRAENI	Teknik Informatika (S1)
29	2155762663131103	FERDIANSYAH	Teknik Informatika (S1)
30	0537746647130122	GUNAWAN PRIA UTAMA	Teknik Informatika (S1)
31	0740763664130282	HADIDTYO WISNU WARDANI	Teknik Informatika (S1)
32	9838763664130292	HARIS MUNANDAR	Teknik Informatika (S1)



33	0652765666130282	HILLMAN AKHYAR DAMANIK	Teknik Informatika (S1)
34	0434764665230262	IKA SUSANTI	Teknik Informatika (S1)
35	8949771672130282	IKHSAN RAHDIANA	Teknik Informatika (S1)
36	7437754655230112	IMELDA	Teknik Informatika (S1)
37	2654764665130222	INDRA	Teknik Informatika (S1)
38	7454765666130203	INDRA HERTANTO	Teknik Informatika (S1)
39	9456761662130143	JOKO CHRISTIAN	Teknik Informatika (S1)
40	5460755656230082	LESTARI MARGATAMA	Teknik Informatika (S1)
41	5540767668230303	MEPA KURNIASIH	Teknik Informatika (S1)
42	4562753654230103	MERRY ANGGRAENI	Teknik Informatika (S1)
43	2453748649130073	MOHAMMAD ANIF	Teknik Informatika (S1)
44	2961757659200032	MUFTI	Teknik Informatika (S1)
45	1961760661130172	MUHAMMAD AINUR RONY	Teknik Informatika (S1)
46	4537746647130113	NANO PRAMONO SOERYONEGORO	Teknik Informatika (S1)
47	4554760661230252	PIPIN FARIDA ARIYANI	Teknik Informatika (S1)
48	4151756657130113	PURWANTO	Teknik Informatika (S1)
49	8540769670230272	PUTRI HAYATI	Teknik Informatika (S1)
50	2362766667131233	RAHMAT OKTAVIAN	Teknik Informatika (S1)
51	0949761662230182	REVA RAGAM SANTIKA	Teknik Informatika (S1)
52	1660744645230082	RIRIT ROESWIDIAH	Teknik Informatika (S1)
53	1745767668230302	RISKIANA WULAN	Teknik Informatika (S1)
54	2959764665237002	RIZKA TIAHARYADINI	Teknik Informatika (S1)
55	4943758659130162	RIZKY TAHARA SHITA	Teknik Informatika (S1)
56	4554753654230092	SAFRINA AMINI	Teknik Informatika (S1)
57	9937760661130262	SEJATI WALUYO	Teknik Informatika (S1)
58	0246748649131143	SUBANDI	Teknik Informatika (S1)
59	0246748649131143	SUBANDI	Teknik Informatika (S1)
60	5937767668130372	SYAMSUDIN ZUBAIR	Teknik Informatika (S1)
61	6447751652130113	UTOMO BUDIYANTO	Teknik Informatika (S1)
62	4639763664130282	WAHYU PRAMUSINTO	Teknik Informatika (S1)
63	4749764665137022	WINDARTO	Teknik Informatika (S1)
64	7854758659230162	WINDHY WIDHYANTY	Teknik Informatika (S1)
65	6945763664130252	YUDI WIHARTO	Teknik Informatika (S1)
66	6952768669130332	ZAQI KURNIAWAN	Teknik Informatika (S1)
67	5454763664230162	AGNES ARYASANTI	Sistem Informasi (S1)
68	1947743644130112	AGUNG PRIHARTONO	Sistem Informasi (S1)
69	8141761662130183	AGUS UMAR HAMDANI	Sistem Informasi (S1)
70	8947761662230262	ANITA DIANA	Sistem Informasi (S1)
71	6647764665131142	ARI SAPUTRO	Sistem Informasi (S1)



72	5251757658130183	ASEP ABDUL ROHMAN	Sistem Informasi (S1)
73	7752762663237012	ATIK ARIESTA	Sistem Informasi (S1)
74	9846770671130352	BAYU SATRIA PRATAMA	Sistem Informasi (S1)
75	9551750651130082	BRURI TRYA SARTANA	Sistem Informasi (S1)
76	2555742643130063	BULLION DRAGON ANDAH	Sistem Informasi (S1)
77	5560751652130083	DENI MAHDIANA	Sistem Informasi (S1)
78	3535770671130233	DEVIT SETIONO	Sistem Informasi (S1)
79	1542762663230293	DEWI KUSUMANINGSIH	Sistem Informasi (S1)
80	4454761662130162	DIAN ANUBHAKTI	Sistem Informasi (S1)
81	7637741642130122	DJATI KUSDIARTO	Sistem Informasi (S1)
82	3453751652130073	BIMA CAHYA PUTRA	Sistem Informasi (S1)
83	2538753654130102	GANDUNG TRIYONO	Sistem Informasi (S1)
84	4751753654230082	GRACE GATA	Sistem Informasi (S1)
85	8857759660131082	HENDRI IRAWAN	Sistem Informasi (S1)
86	4735758659130162	HUMISAR HASUGIAN	Sistem Informasi (S1)
87	7746771672230342	INDAH PUSPASARI HANDAYANI	Sistem Informasi (S1)
88	6435760661230183	ITA NOVITA	Sistem Informasi (S1)
89	1944770671130422	JEREMY JONATHAN	Sistem Informasi (S1)
90	2935754655130132	JOKO SUTRISNO	Sistem Informasi (S1)
91	2851769670130282	KUKUH HARSANTO	Sistem Informasi (S1)
92	9849754655130112	LAUW LI HIN	Sistem Informasi (S1)
93	6849759660131132	LIS SURYADI	Sistem Informasi (S1)
94	863976566237002	MARINI	Sistem Informasi (S1)
95	0643760661230242	MOTIKA DIAN ANGGRAENI	Sistem Informasi (S1)
96	7050757658237093	NAWINDAH	Sistem Informasi (S1)
97	6050754655230123	NIDYA KUSUMAWARDHANY	Sistem Informasi (S1)
98	3547763664230252	NOFIYANI	Sistem Informasi (S1)
99	5037758659230233	NONI JULIASARI	Sistem Informasi (S1)
100	4847756657231432	NURWATI	Sistem Informasi (S1)
101	1834757658230202	PAINEM	Sistem Informasi (S1)
102	2543764665230232	PEPI PERMATASARI	Sistem Informasi (S1)
103	5947771672230352	RATNA KUSUMAWARDANI	Sistem Informasi (S1)
104	3537759660230223	RATNA UJIAN DARI	Sistem Informasi (S1)
105	4656758659230152	RETNO WULANDARI	Sistem Informasi (S1)
106	4456766667130233	RIZKY PRADANA	Sistem Informasi (S1)
107	6249760661230213	SAFITRI JUANITA	Sistem Informasi (S1)
108	4261760661230183	SAMSINAR	Sistem Informasi (S1)
109	0241752653237043	SRI MULYATI	Sistem Informasi (S1)
110	3542749650230153	SRI WAHYUNINGSIH	Sistem Informasi (S1)



111	5539750651131093	TEJA ENDRA ENG TJU	Sistem Informasi (S1)
112	7552757658230133	TITIN FATIMAH	Sistem Informasi (S1)
113	7449765666230222	TRI IKA JAYA KUSUMAWATI	Sistem Informasi (S1)
114	9758748649230072	WIWIN WINDIHASTUTY	Sistem Informasi (S1)
115	2257766667230243	WULANDARI	Sistem Informasi (S1)
116	3948765666230332	YESI PUSPITA DEWI	Sistem Informasi (S1)
117	0448750651130092	YUDI SANTOSO	Sistem Informasi (S1)
118	4057766667230303	YULIANAWATI	Sistem Informasi (S1)
119	7061753654230083	YULIAZMI	Sistem Informasi (S1)
120	9043744645130083	GATOT PURWANTO	Sistem Komputer (S1)
121	3941771672130302	IMAN PERMANA	Sistem Komputer (S1)
122	0537752653130122	IRAWAN	Sistem Komputer (S1)
123	0443759660230253	RIRI IRAWATI	Sistem Komputer (S1)
124	7863755656130092	YANI PRABOWO	Sistem Komputer (S1)

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