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Business Intelligence Dashboard Using Power BI for Sentiment Analysis and Tokopedia Product Performance

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ABSTRACT

Customer reviews on e-commerce platforms provide valuable insights into product performance and consumer satisfaction. However, most existing studies focus primarily on sentiment classification and model evaluation, with limited integration of sentiment data and business indicators such as product price, sales volume, and category. This study developed a Business Intelligence (BI) dashboard using Microsoft Power BI to analyze Tokopedia product performance by integrating customer sentiment, ratings, product prices, categories, review counts, and sold counts. A descriptive quantitative approach was employed using a secondary dataset consisting of 65,543 reviews, 5,521 products, 856 anonymous shops, and 13 attributes. Sentiment labels were transformed into numerical sentiment scores (positive = 1, neutral = 0, negative = −1) through a rule-based mapping method to support quantitative analysis. The research process included data inspection, preprocessing, sentiment score transformation, data modeling, dashboard development, correlation analysis, and functional evaluation. Results showed that positive sentiment dominated the dataset, accounting for 97.56% of all reviews. The Food and Beverage category recorded the highest review volume and average sold count, while Electronics had the highest average product price. Spearman correlation analysis revealed a moderate negative relationship between product price and sold count (−0.443) and a strong positive relationship between review count and sold count (0.722). The dashboard supports data-driven product evaluation, pricing, and marketing decisions.

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1. Introduction

The rapid growth of e-commerce has significantly increased the volume of digital transactions, resulting in the generation of large amounts of customer review data. These data not only contain textual comments but also include various supporting attributes such as product ratings, product prices, product categories, review counts, and sold counts. Customer reviews serve as an important source of information for understanding consumer experiences, preferences, and satisfaction levels regarding products and services. For sellers and marketplace managers, such information can provide valuable insights into product performance and customer perceptions. However, review data are often stored as raw tabular datasets, making them difficult to interpret quickly and effectively for business decision-making purposes. As the amount of data continues to grow, the need for tools that can transform complex datasets into meaningful and actionable information becomes increasingly important.

Sentiment analysis has emerged as a widely adopted approach for classifying customer opinions into positive, neutral, and negative categories. In the context of e-commerce marketplaces, sentiment analysis can assist sellers, platform administrators, and business analysts in identifying consumer attitudes toward products and services. Previous studies have employed a variety of machine learning and artificial intelligence approaches for sentiment classification, including Support Vector Machine, Naive Bayes, Random Forest, deep learning models, transformer-based architectures, large language models, ensemble learning methods, and multilingual approaches to analyze e-commerce product reviews [1]-[4], [6], [10], [11], [13]-[17], [19], [20], [24], [26]. These studies have demonstrated the effectiveness of computational methods in extracting sentiment information from textual data and improving classification performance. Specifically, within the Tokopedia marketplace context, previous research has investigated sentiment analysis of product reviews using the Support Vector Machine algorithm [1].

Despite the continuous advancement of sentiment analysis research, most existing studies primarily focus on text classification performance and model evaluation metrics. While these aspects are important from a technical perspective, business users often require more comprehensive insights than sentiment labels alone. In practical decision-making scenarios, managers and analysts need to understand how sentiment relates to other business indicators, such as product price, rating, review count, product category, and sold count. Positive sentiment does not always correspond to high sales performance, and products with premium prices do not necessarily receive a large number of reviews. Furthermore, different product categories may exhibit distinct purchasing behaviors and consumer response patterns. Therefore, analyzing sentiment independently from other business indicators may limit the usefulness of the information generated for strategic decision-making.

Business Intelligence (BI) offers an effective solution for transforming raw data into meaningful visual information that can support data-driven decision-making. BI dashboards enable users to monitor key performance indicators, compare product categories, identify trends and patterns, and interactively explore data from multiple perspectives. Through visual analytics, complex relationships among variables can be understood more efficiently than through traditional tabular reports. Previous studies have demonstrated that Power BI dashboards can be successfully applied in various domains, including inventory visualization, organizational performance monitoring, financial performance evaluation, social trend analysis, vehicle loss monitoring, micro-enterprise development, and business forecasting applications [5], [7]-[9], [12], [18], [22], [23], [25]. These findings indicate that Power BI is a relevant and effective platform for data visualization and performance analysis across different business environments.

Based on these challenges and opportunities, this study develops a Business Intelligence dashboard using Microsoft Power BI to analyze customer sentiment and product performance within the Tokopedia marketplace. The proposed dashboard integrates multiple data dimensions, including review text, sentiment labels, product ratings, product prices, product categories, review counts, and sold counts into a unified analytical platform. By combining sentiment information with business performance indicators, users can gain a more comprehensive understanding of product performance and consumer behavior. This integration allows stakeholders to evaluate not only how consumers feel about products but also how those perceptions relate to actual marketplace performance.

The novelty of this research lies in the integration of sentiment analysis with product performance indicators within a single Business Intelligence environment, as well as the separation of analytical perspectives between review-level data and product-level data. This distinction is important because a single product can generate multiple reviews, while attributes such as product price and sold count are associated with the product level rather than the review level. Separating these analytical levels helps prevent misinterpretation and enables more accurate analysis of marketplace performance. Therefore, the objective of this study is to develop a Power BI dashboard capable of presenting key performance indicators, sentiment distributions, product category comparisons, price and sales patterns, and relationships among variables. The resulting dashboard is expected to help sellers, platform managers, and business analysts evaluate marketplace product performance more efficiently, systematically, and through a data-driven approach.

2. Research Method

This study employed a descriptive quantitative approach combined with the design and development of a Business Intelligence dashboard. The quantitative approach was selected because the analyzed variables consisted of numerical data, including product price, rating, sold count, review count, and sentiment score. The descriptive approach was applied to explain the characteristics of the dataset, sentiment distribution, product category comparisons, price and sales patterns, and relationships among variables. The study did not aim to establish causal relationships but rather to provide a comprehensive overview of product performance and customer sentiment based on available marketplace data.

2.1 Research Dataset

The dataset used in this study was a secondary dataset of Tokopedia product reviews collected in 2025. The dataset consisted of 65,543 reviews, 13 attributes, 5,521 unique products, and 856 anonymous shops. The main attributes included review text, review date, review ID, product name, product category, product variant, product price, product URL, product ID, rating, sold count, shop ID, and sentiment label.

Textual data were represented by the review text attribute. Categorical data included product category and sentiment label, while numerical data consisted of product price, rating, and sold count. The sentiment label variable was used to represent customer opinions. Product price and sold count were used to evaluate product performance in terms of pricing and sales volume, whereas rating served as an indicator of customer evaluation and satisfaction.

The review dates ranged from November 18, 2015, to December 12, 2025. Therefore, the dataset was treated as a snapshot dataset rather than a longitudinal dataset. Consequently, sold count was not analyzed as a periodic transaction variable but as an indicator of the total number of products sold at the time the data were collected.

2.2 Data Preprocessing

Data preprocessing was conducted to ensure that the dataset could be analyzed consistently and accurately within Power BI. This stage included column structure inspection, missing value detection, duplicate checking, data type adjustment, and sentiment score transformation. Missing value analysis focused on the primary variables used in the study, namely sentiment label, product price, sold count, rating, product ID, and product category.

The results indicated that no missing values were found in the main analytical variables. Missing values were identified only in the product variant attribute; however, this variable was not used as a primary factor in the analysis. No duplicate records were detected in either the review ID field or across complete data rows. The review date column was converted into a date data type, while product price and sold count were converted into numeric data types. The rating variable was maintained as a numerical attribute.

The sentiment label column in the secondary dataset already contained sentiment classification results obtained through a lexicon-based labeling process using an Indonesian sentiment dictionary. A lexicon-based approach was adopted because the dataset had been previously labeled, and therefore no retraining of sentiment classification models was required in this study. To facilitate quantitative analysis alongside other numerical variables, the sentiment label attribute was transformed into a sentiment score using a rule-based mapping approach. This transformation enabled sentiment information to be analyzed together with product price, rating, review count, and sold count. The “Positive” label was mapped to a score of 1, the “Neutral” label to a score of 0, and the “Negative” label to a score of −1.Tabel 1. Transformasi Skor Sentimen

Label	Sentimen Score	Interpretasi
Positive	1	Respons positif
Neutral	0	Respons netral
Negative	-1	Respons negatif

2.3 Data Modeling

Data modeling was conducted to minimize potential calculation bias during the analysis process. The original dataset was structured at the review level, meaning that a single product could appear multiple times because it may have received numerous customer reviews. If variables such as product price and sold count were calculated directly from all review records, products with a large number of reviews could exert a disproportionate influence on the analytical results.

To address this issue, the data model was divided into two main tables: **FactReviews** and DimProduct. The **FactReviews** table stores data at the review level, while the **DimProduct** table stores data at the product level. A relationship between the two tables was established using the **product ID** attribute as the primary key. This separation of fact and dimension tables follows common Business Intelligence dashboard design practices, which distinguish transactional data from analytical entities [7], [23], [25].

The **FactReviews** table contains review ID, review text, review date, product ID, rating, sentiment label, and sentiment score. Meanwhile, the **DimProduct** table includes product ID, product name, product category, product price, sold count, and shop ID. This data model enables analysis to be performed at two different levels. The review level is used to analyze customer opinions and sentiment patterns, whereas the product level is used to evaluate product price, sold count, review count, and average sentiment score without repeatedly counting the same product. As a result, the model provides a more accurate representation of product performance and customer feedback.

2.4 Dashboard Design

The dashboard was developed using Microsoft Power BI Desktop. The design process was based on user requirements for monitoring key performance indicators, understanding sentiment distribution, comparing product categories, and exploring relationships among product price, rating, review count, and sold count.

The dashboard was organized into four main pages. The first page, **Overview**, presents high-level performance indicators, including total reviews, number of unique products, number of anonymous shops, average rating, average product price, and average sold count. This page provides users with a general understanding of the dataset and overall marketplace performance.

The second page, **Sentiment Analysis**, focuses on customer opinions and sentiment trends. It displays sentiment distribution, sentiment composition across product categories, and rating distribution. This page allows users to identify dominant sentiment patterns and evaluate customer satisfaction across different product segments.

The third page, **Price and Sales**, presents product pricing and sales performance information. Various visualizations are used to illustrate product price distributions, sold count patterns, and category-level comparisons, enabling users to identify products or categories with strong market performance.

The fourth page, **Correlation and Insight**, examines the relationships among sentiment score, product price, sold count, review count, and rating. This page is intended to support exploratory analysis by helping users identify potential associations and trends among key business variables.

To enhance analytical flexibility, the dashboard includes interactive slicers based on product category, sentiment label, rating, product price, and review date. These filtering features allow users to customize the displayed information according to specific analytical needs and explore the dataset from multiple perspectives.

Table 2. Dashboard page design

Page	Main Visual	Objective	Status
Overview	KPI, bar chart, donut chart	Displays a summary of key indicators	Fulfilled
Sentiment Analysis	Donut chart, stacked bar chart	Displays sentiment distribution	Fulfilled
Price and Sales	Barchart, scatter plot	Displays price patterns and sold counts	Fulfilled
Correlation and Insight	Matrix, scatter plot	Displays relationships between variables	Fulfilled

2.5 Correlation Analysis

Correlation analysis was conducted to determine the direction and strength of the relationship between sentiment score, product price, sold count, review count, and rating. This study used Pearson correlation and Spearman correlation. Pearson correlation is used to interpret linear relationships, while Spearman correlation is used to interpret relationships based on ranking. Spearman correlation is important because product price and sold count have a wide distribution and extreme values.

Correlation analysis was conducted at the review level and the product level. At the review level, the analysis used all review rows. At the product level, the analysis used unique product data. This separation is necessary because sentiment score is at the review level, while product price and sold count are inherently at the product level..

3. Result and Discussion

3.1 Dataset Characteristics

Initial inspection results indicate that the dataset contains a large enough amount of data for analysis using a Business Intelligence approach. The dataset consists of 65,543 reviews, 13 attributes, 5,521 unique products, and 856 anonymous stores. The data includes review text, review date, product name, product category, product price, product ID, rating, sold count, shop ID, and sentiment label.

The dataset is dominated by positive sentiment. Positive sentiment comprises 63,943 reviews, or 97.56%. Neutral sentiment comprises 802 reviews, or 1.22%. Negative sentiment comprises 798 reviews, or 1.22%. Five-star ratings also dominate, accounting for 61,525 reviews, or 93.87%. This indicates that the majority of consumers in the dataset responded positively to the products they purchased.

The dominance of positive sentiment should be interpreted with caution. Class imbalance can limit the variation in sentiment scores and affect the interpretation of statistical relationships. Previous research also emphasized that data imbalance and review variation are important challenges in e-commerce sentiment analysis [4], [6], [13], [19]..

Table 3. Summary of dataset, sentiment, and ratings

Indicators	Category	Value
Total reviews	All data	65,543
Total attributes	All data	13
Unique products	All data	5,521
Anonymous stores	All data	856
Date range	Review date	November 18, 2015 to December 12, 2025
Sentiment	Positive	63,943 or 97.56%
Sentiment	Neutral	802 or 1.22%
Sentiment	Negative	798 or 1.22%
Rating	5 stars	61,525 or 93.87%

3.2 Power BI Dashboard Design Results

The Business Intelligence dashboard is designed to transform Tokopedia product review data into easy-to-read visuals. The dashboard not only displays summary figures but also helps users understand sentiment patterns, product category differences, price, sold count, rating, number of reviews, and relationships between variables.

The Overview page presents key indicators through KPI cards. This page allows users to view total reviews, number of unique products, number of anonymous stores, average rating, average product price, and average sold count. Category and sentiment visualizations help users quickly understand the composition of the data..

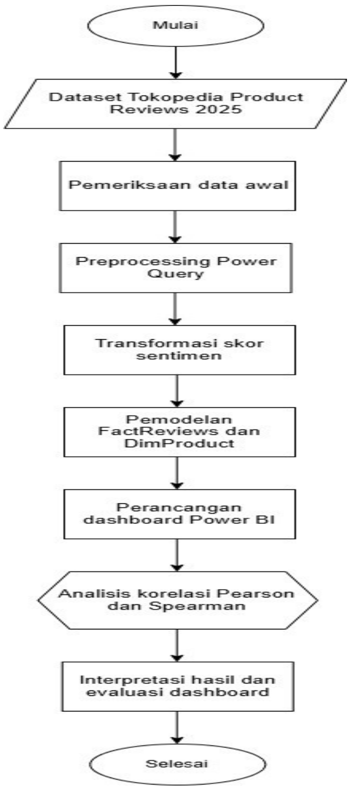

Figure 1. Research flow diagram

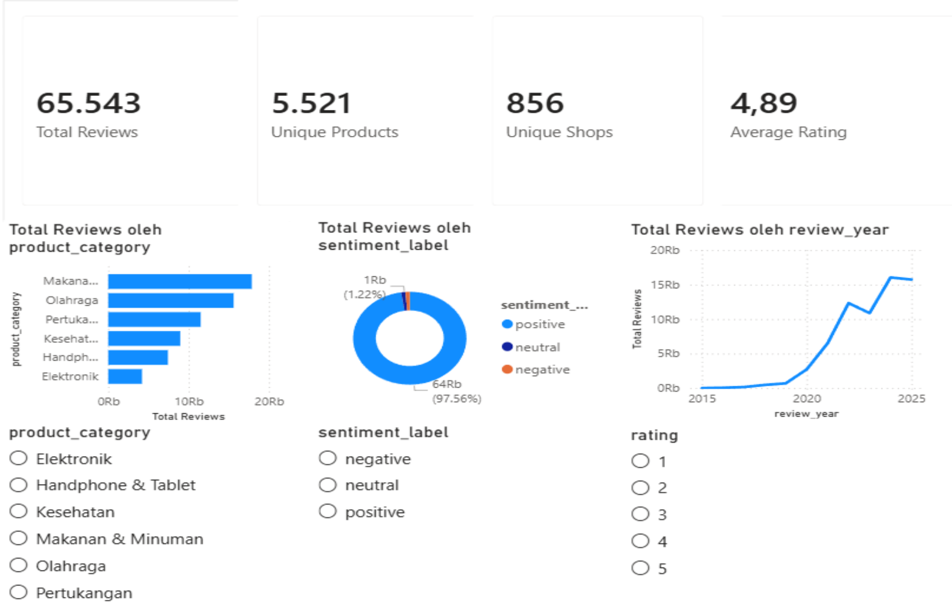

Figure 2. Power BI dashboard homepage

The dashboard fulfills the primary function of Business Intelligence by presenting data in a concise, structured, and interactive format. The use of slicers allows users to filter data based on product category, sentiment, rating, price, or review date range. This interactive feature strengthens the dashboard's function as a data exploration tool [7]-[9], [23].

3.3 Consumer Sentiment Distribution

Sentiment distribution is a primary focus because consumer reviews represent purchasing experiences. Positive sentiment indicates a good experience. Neutral sentiment indicates an assessment that is neither strongly positive nor negative. Negative sentiment indicates potential consumer complaints.

The analysis results show that 63,943 reviews, or 97.56%, were labeled positive. Neutral sentiment accounted for 802 reviews, or 1.22%. Negative sentiment accounted for 798 reviews, or 1.22%. These results indicate that the majority of consumers responded favorably to the products they purchased. However, the predominance of positive sentiment also tends to weaken the relationship between sentiment scores and other variables.

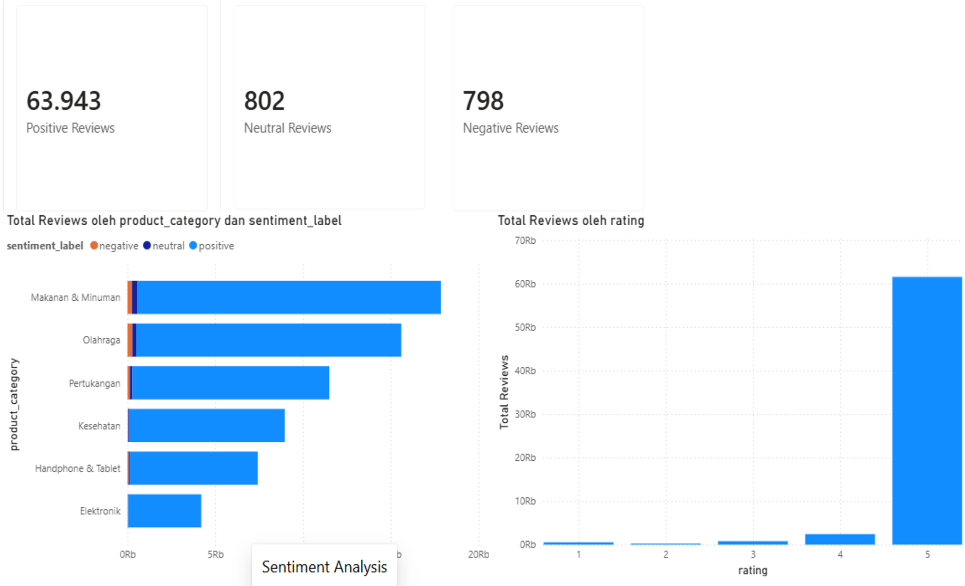

Figure 3. Distribution of Tokopedia product review sentiment

The unbalanced distribution of sentiment explains why sentiment scores cannot be the sole indicator of product performance. When the majority of scores are 1, data variation is limited. Therefore, sentiment needs to be analyzed alongside rating, price, number of reviews, product category, and sold count. This approach aligns with recent e-commerce studies that emphasize the need to understand consumer reviews contextually, not solely through sentiment labels [2], [3], [10], [17], [24].

3.4 Product Analysis by Category

Product category analysis was conducted to identify the most dominant product groups in the dataset. Comparisons were made based on the number of reviews, number of unique products, percentage of positive sentiment, percentage of negative sentiment, average rating, average product price, and average sold count.

The analysis results show that the Food & Beverage category has the highest number of reviews, with 17,859 reviews. This category also has the highest average sold count at the product level, with 3,560. The Electronics category has the highest average price, with 4,701,444, but a lower average sold count, with 411. These results indicate that categories with lower prices tend to have higher purchase activity and reviews.

Table 4. Product Category Indicators at the Product Level

Categories	Number of Reviews	Positif (%)	Negatif (%)	Average Rating	Average Price	Average Sold Count
Food and Beverages	17.859	96,90	1,47	4,878	79.123	3.899
Sports	15.600	96,76	1,78	4,851	327.260	667
Handicrafts	11.500	97,57	1,16	4,892	277.987	1.616
Health	8.959	98,85	0,44	4,940	133.629	2.430
Mobile Phones and Tablets	7.423	98,49	0,84	4,933	1.340.294	370
Electronics	4.202	98,93	0,57	4,953	3.491.541	1.188

Positive sentiment was high across all categories. The Electronics category had a positive percentage of 99.56%, while Food & Beverages had a positive percentage of 96.77%. This difference indicates that positive sentiment does not always align with the sales count. The Electronics category had high positive sentiment, but its average sales count was not as high as Food & Beverages. Therefore, product performance analysis needs to combine sentiment and other business indicators.

3.5 Price, Sold Count, and Correlation Analysis

Price and sales count analysis was conducted to identify patterns between price levels and product sales volume. The visualization results show that categories with low average prices tend to have higher average sales counts. Food & Beverages products had lower average prices and the highest average sales counts. Conversely, Electronics products had the highest average prices and lower sales counts.

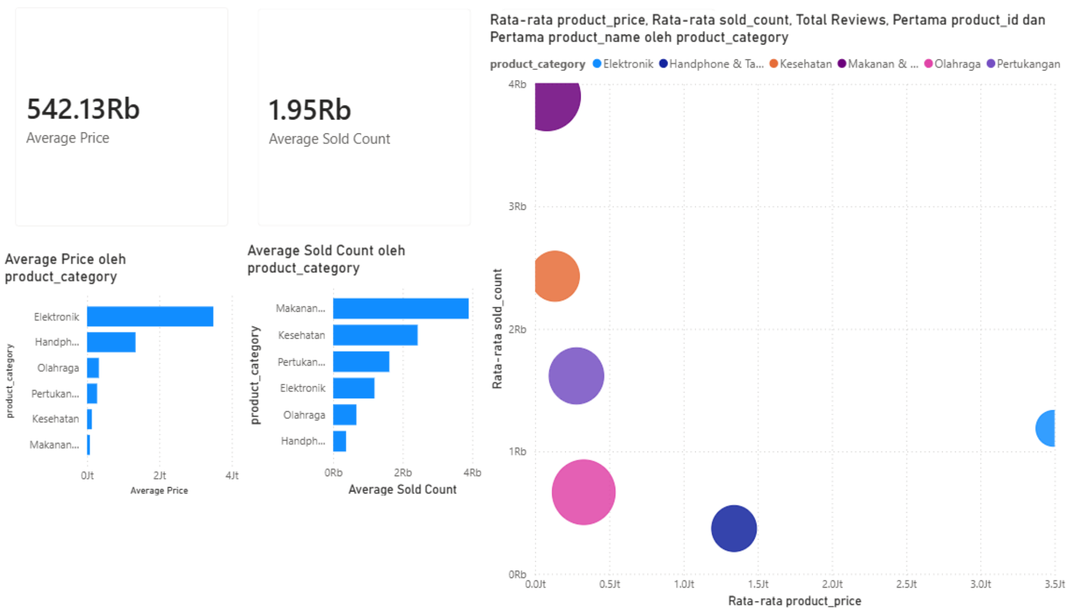

Figure 4. Visualization of product price and sold count

This pattern suggests that price and sold count need to be interpreted contextually. Products with lower prices are more likely to be purchased repeatedly. Products with higher prices typically require greater purchase consideration. Therefore, the dashboard should provide category slicers so users can distinguish patterns between product groups.

Correlation analysis strengthens the visualization results. At the review level, the relationship between sentiment score and product price has a Pearson's 0.022927 and a Spearman's 0.028845. These values indicate a very weak positive relationship. The relationship between sentiment score and sold count is also very weak, with a Pearson's 0.009659 and a Spearman's 0.045832.

At the product level, the relationship between product price and sold count has a Pearson correlation of -0.018234 and a Spearman correlation of -0.442985. The Spearman correlation indicates a moderate negative correlation. This means that products with higher prices tend to have lower sold counts based on the ranking data. The relationship between review count and sold count has a Pearson correlation of 0.077545 and a Spearman correlation of 0.722089. The Spearman correlation indicates a strong positive correlation. This means that products with higher sold counts tend to have more reviews.

Table 5. Correlation analysis results

Analysis Level	Variable Pairs	Pearson	Spearman	Meaning
Review	Sentiment score and product price	0,022927	0,028845	Very weak positive
Review	Sentiment score and sold count	-0,009659	-0,045832	Very weak negative
Review	Product price and sold count	-0,018340	-0,409447	Moderate negative
Product	Avg sentiment score and product price	0,060829	0,102191	Weak positive
Product	Avg sentiment score and sold count	-0,030128	-0,313578	Moderate negative
Product	Product price and sold count	-0,018234	-0,442985	Moderate negative
Analysis Level	Review count and sold count	0,077545	0,722089	Strong positive

The difference in Pearson and Spearman's results indicates that the relationship between variables is not always linear. Spearman's analysis was more informative in this study because product price and sold count had a wide distribution. This finding supports the need for an interactive dashboard that not only displays correlation figures but also provides visualizations and filters to interpret the data context.

3.6 Dashboard Evaluation

The dashboard was evaluated functionally by matching visual features to analysis needs. The dashboard was assessed based on its ability to display key indicators, sentiment distribution, product category comparisons, price and sold count patterns, relationships between variables, and interactive features.

The dashboard met the need for key indicators through KPI cards. The dashboard also met sentiment analysis needs by visualizing the distribution of positive, neutral, and negative sentiment. In terms of categories, the dashboard can compare the number of reviews, average price, average rating, and average sold count for each product category.

In terms of relationships between variables, the dashboard presents patterns of product price, sold count, review count, rating, and sentiment score through visualizations and correlation tables. The slicer feature allows users to filter data based on product category, sentiment, rating, price, and review date. This interactivity makes the dashboard more flexible than static reports.

Table 6. Functional evaluation of the dashboard

Evaluation Aspect	Result
Main indicators	The dashboard displays total reviews, unique products, anonymous stores, average rating, average price, and average sold count.
Sentiment distribution	The dashboard displays the number and percentage of positive, neutral, and negative sentiments.
Category comparison	The dashboard displays category comparisons based on review count, rating, price, and sold count.

Evaluation Aspect	Result
Price and sales pattern	The dashboard displays price and sold count patterns through category visualization and scatter plots.
Correlation insight	The dashboard displays Pearson, Spearman, and interpretation of relationships between variables.
Interactivity	The dashboard provides slicers for categories, sentiment, rating, price, and review date.

The Interactivity Dashboard provides slicers for categories, sentiment, ratings, prices, and review dates.

While the dashboard meets the functional requirements, this study has several limitations. The dataset used is secondary, so the researcher lacked control over the data collection and sentiment labeling process. Sold count is also treated as a snapshot indicator, not periodic transaction data. Furthermore, the dashboard does not include variables such as promotions, discounts, shipping costs, store reputation, seller location, and product position in marketplace search results.

The developed dashboard has potential for real-world applications for various e-commerce business stakeholders. For sellers, the dashboard can be used to regularly monitor product review sentiment and compare performance across categories to determine product development priorities. For platform managers, the dashboard allows identification of categories with high consumer complaint rates based on the percentage of negative sentiment, thus supporting product curation policies. For business analysts, the dashboard provides a visualization of the relationship between price, number of reviews, and sold count, which can be used to inform pricing and marketing strategy recommendations. The interactive slicer feature on the dashboard also allows users to independently explore the data without requiring specialized technical expertise, supporting broader data-driven decision-making.

4. Conclusion

This research successfully designed a Business Intelligence dashboard using Microsoft Power BI to analyze Tokopedia's product sentiment and performance. The developed dashboard displays key indicators, sentiment distribution, product category comparisons, price and sold count patterns, and relationships between variables in a concise and interactive visual format.

The analysis results show that the dataset is dominated by positive sentiment (97.56%) and 5-star ratings (93.87%). The Food & Beverage category has the highest number of reviews and average sold count. The Electronics category has the highest average price. These findings indicate that lower-priced categories tend to have higher purchase and review activity than higher-priced categories.

The correlation results indicate that sentiment score has a very weak relationship with both product price and sold count. Conversely, product price and sold count have a moderate negative relationship based on the Spearman correlation. Review count and sold count have a strong positive relationship. These findings demonstrate that marketplace product performance cannot be assessed solely by consumer sentiment. Product performance needs to be analyzed in conjunction with price, number of reviews, rating, product category, and sold count.

Future research could expand the dashboard by adding variables such as promotions, discounts, shipping costs, store reputation, seller location, and usability evaluations by end-users. Future research could also use periodic transaction data to analyze sales patterns over time.

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