

## Implementation of Business Intelligence in Analyzing Consumer Behavior: A Study of the Property Business

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### ABSTRACT

This study aims to analyze the implementation of business intelligence in understanding consumer behavior. Research data were collected through observation, interviews, and documentation, then processed using clustering techniques based on the K-Means algorithm and visualized through an analytics dashboard using Microsoft Power Business Intelligence. The research method employed is Research and Development (R&D) with the 4D model (Define, Design, Develop, Disseminate). This study integrates customer relationship management and machine learning as tools to manage, analyze, and visualize consumer behavior data. The results indicate that the application of business intelligence can group consumers into eight clusters based on behavioral patterns and transaction characteristics. The resulting analytics dashboard assists property management in making strategic decisions more efficiently. Furthermore, the use of business intelligence has been proven to enhance effectiveness in understanding consumer preferences, optimizing data management, and supporting marketing strategies. This study recommends implementing data-driven technology to increase the company's competitiveness amid increasingly intense business competition.

**Keywords:** Business Intelligence, Consumer Behavior, Research and Development (R&D), Machine Learning, Microsoft Power BI

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### INTRODUCTION

Consumer behavior essentially aims to examine the reasons behind consumers' actions and the decisions they make. This reality highlights the diversity of consumers, making it an intriguing subject of study as it involves individuals from various age ranges, cultures, educational backgrounds, and socioeconomic conditions. Consumer behavior patterns and purchasing preferences have become increasingly complex and diverse, rendering traditional marketing strategies inadequate to meet individualized needs (Wang, 2025). Goal-oriented individual behavior is primarily determined by behavioral intention (Nurmalasari et al., 2025). This intention is shaped through various processes, including motivation or desire to act, volitional attitudes toward behavior and subjective norms, non-volitional perceived behavioral control, anticipated emotions of positive and negative feelings, as well as habits formed by the frequency or infrequency of past behavior (Han, 2021).

Therefore, it is crucial to study how consumers behave through tools capable of comprehensively understanding their behavior. However, there has yet to be a tool that effectively provides a clear depiction of consumer behavior. Consumer behavior refers to a series of individual activities directly related to the acquisition and use of goods or services, including the decision-making processes underlying the planning and execution of these activities (Sanusi et al., 2023).

Consumer behavior involves buyers' actions to spend money over a long period and their efforts to recommend a product to others. The preferences and determination of buyers for future purchases are also part of consumer behavior. Consumers' responses to products or services offered by companies, and their efforts to remain loyal customers, are likewise recognized as consumer behavior (Roy, 2022).

Understanding consumer behavior is essential for facing the increasingly fierce competition within the business industry. With technological advancements, businesses continuously strive to improve production quality and marketing management to achieve profit targets. Competition has spread across all business sectors, making rivalry between companies increasingly intense. One of the most vital aspects of business is marketing strategy; an effective strategy determines a company's market position and sales volume. Examples of applicable marketing strategies include utilizing search engines such as Google, implementing affiliate programs, leveraging social media platforms, optimizing content, and collaborating with influencers (Rakib, 2016). When properly executed, businesses can generate maximum profits; conversely, ineffective marketing strategies may lead to decreased sales and reduced revenue.

Marketing efforts aimed at preventing corporate losses are strongly influenced by consumer behavior. The implementation of business intelligence enables companies to understand consumer behavior more intelligently and make data-driven decisions. Essentially, business intelligence is a tool developed to analyze consumer behavior, providing interactive access to data and equipping managers with analytical capabilities for business decision-making. The primary objective of implementing business intelligence tools is to enhance the overall organizational impact and improve operational efficiency; nonetheless, additional benefits may also be achieved if the technology is appropriately utilized (Selvarajan, 2024). Business intelligence offers several essential features that succeed traditional consumer behavior analysis, especially when dealing with complex and large-scale data that require visualization for easier interpretation (Rosário & Dias, 2023). Among these features are customer relationship management (CRM) systems, which, when combined with analytical dashboards and machine learning applications, can maximize CRM performance in supporting purchase-decision analysis.

The analysis of customer relationship management using decision-support applications such as analytical dashboards and machine learning is optimized to understand consumer behavior at PT. Asera Properti. At PT. Asera Properti, high-velocity data inflows must be processed quickly, making business intelligence an essential tool for the company. The main issue faced by PT. Asera Properti as identified in this research phenomenon is limited data access, indicating that the company cannot fully observe consumer behavior. To address this, business intelligence plays a central role in analyzing consumer behavior at PT. Asera Properti based on the available data.

PT. Asera Properti faces challenges in the highly competitive global market due to insufficient consumer engagement and limited creativity and innovation in product introduction. The core issue lies in the absence of an information system capable of identifying consumer behavior to generate relevant creative solutions for business needs. Consumers' purchasing decisions are influenced by their perceptions of brand image and pricing. The aspects affecting consumer purchasing decisions can be analyzed through marketing strategies involving product characteristics, pricing, and promotional activities, as well as consumer behavior dimensions such as cultural, social, and psychological factors (Sostar and Ristanović, 2023).

The most appropriate solution to these problems is the implementation of business intelligence to effectively analyze consumer behavior. This research serves as an input for PT. Asera Properti, emphasizing business intelligence systems that integrate customer relationship management with decision-making tools such as analytical dashboards and machine learning applications.

## **LITERATURE REVIEW**

### **Consumer Behavior**

Consumer behavior can be defined as the direct actions taken by consumers in evaluating, selecting, acquiring, and using the goods or services they desire (Sigar et al., 2021). Consumers'

decisions and preferences are formed by various factors, both internal and external. The diversity of consumer needs and wants may change over time due to several influencing factors that affect their purchasing decisions (Azzahrah et al., 2023). Therefore, marketers need to deeply understand consumer behavior so that marketing strategies can be effectively implemented and achieve optimal results.

### **Business Intelligence**

Business intelligence is a structured framework that begins with data storage, integrates data collected from various sources, and presents it as useful information to support decision-making (Lloyd, 2011). Business intelligence offers several significant benefits in the business world. It enhances data value through effective integration, facilitating analysis and the drawing of conclusions regarding business conditions. Easily accessible and comprehensible information supports management in making more accurate decisions, helps measure performance, and optimizes operational expenditures.

### **Customer Relationship Manager (CRM)**

Customer Relationship Management (CRM) refers to the process of carefully managing detailed information about individual consumers and all customer “touchpoints” to maximize consumer loyalty. Some companies can reduce costs by directing consumers toward self-service web-based systems. The core objective of CRM is to enhance customer profitability, while in non-profit contexts, it aims to improve operational efficiency or increase customer (Kankam Boadu, 2019).

### **Machine Learning**

In daily activities, humans can easily recognize objects, yet they are not always capable of explaining them in detail. Therefore, the application of machine learning is necessary to assist in the processes of recognition, identification, and prediction of specific data by learning from historical or past datasets (Rosário & Dias, 2023). The concept of machine learning existed even before the 1980s and developed rapidly in the following decades. The evolution of machine learning can be divided into three major eras. The first era, prior to 1980, focused on linear decision surfaces supported by strong theoretical foundations. The second era, during the 1980s, introduced decision trees and artificial neural networks as pioneers of nonlinear learning, though these methods were still theoretically weak and prone to local optimums. Since the 1990s, these approaches have been further developed with stronger foundations in computational learning theory, making them more robust and efficient.

## **METHOD**

This research employs a qualitative approach with the aim of designing a product for consumer behavior analysis through the implementation of business intelligence. The study was conducted at PT. Asera Properti Makassar, from August to October 2024. The research subjects consist of housing purchasers at PT. Asera Properti, selected from data collected over the past three years 2022, 2023, and 2024. These buyers serve as the observation subjects or informants in the study. The study utilizes Customer Relationship Management (CRM) and Machine Learning (ML) to support the implementation of Business Intelligence (BI). The output of the BI system is an analytical dashboard designed to present data visualizations in graphical form. The data collection techniques used in this research include observation and interviews, while the research materials consist of consumer data. To obtain these materials, the researcher employed interviews, preliminary observations, and company documentation. The data analysis technique applied in this study is based on machine learning algorithms, specifically the hierarchical method, which is processed using the Python programming language. The study also includes functionality testing and usability testing to ensure the effectiveness and reliability of the developed analytical dashboard.

## **FINDING AND DISCUSSION**

### **Clustering Analysis**

This research uses data obtained directly from Asera Properti, which is then processed into visualizations in the form of a dashboard using Microsoft Power Business Intelligence Desktop. These visualizations aim to facilitate data analysis and decision-making concerning customers. In

this study, the clustering method is used to group customers based on data, with the K-Means Clustering algorithm as the primary technique.

The clustering process begins with data preprocessing, where raw data is processed to handle missing values using imputation or deletion methods, and standardized with StandardScaler so that each attribute has the same scale. The optimal number of clusters is determined using the Elbow Method or Silhouette Score. After that, the K-Means algorithm is applied by determining the cluster centers randomly, calculating the distance of data to the cluster centers, and updating the cluster centers until convergence is achieved.

**Table 1.** Data Distribution Analysis for Each Cluster

| Cluster | Total Data | Proportion of Data in Each Cluster |
|---------|------------|------------------------------------|
| 7       | 819        | 22,55 %                            |
| 6       | 798        | 21,97 %                            |
| 4       | 660        | 18,17 %                            |
| 5       | 510        | 14,04 %                            |
| 3       | 471        | 12,97 %                            |
| 2       | 220        | 6,06 %                             |
| 1       | 154        | 4,24 %                             |

Based on the clustering results with  $K = 8$ , customers are grouped based on transaction attributes such as interaction frequency and transaction duration. The analysis shows the unique characteristics of each cluster and the strategies required. Cluster 0 requires individual understanding and specific solutions, while Cluster 1 requires an intensive approach to increase engagement. Cluster 2 can be approached with incentives to encourage more active participation, and Cluster 3 requires strengthened communication.

Cluster 4, with moderate interaction frequency, requires product education and consistent follow-up, while Cluster 5 requires structured information and direct assistance during the transaction process. Cluster 6, with high interaction frequency, can be maintained through loyalty programs, while Cluster 7 requires premium services and personalized offers to maintain customer loyalty. With tailored strategies for each cluster, companies can improve the efficiency and quality of customer interactions.

### Descriptive Analysis

#### a. Sales Description Based on Housing Type

This study uses descriptive analysis to provide an overview of data characteristics based on clustering results, including client behavior patterns based on key variables such as interaction frequency, transaction duration, and clusters formed. This analysis provides deep insights into consumer behavior, which forms the basis for strategic decision-making within the company. In addition, sales analysis based on housing type was conducted to understand customer preferences, the contribution of each product, and market potential.

**Table 2.** Housing Dominance in Customer Transactions

| Housing         | Total Data | Proportion of Data in Each Cluster |
|-----------------|------------|------------------------------------|
| Pondok Harapan  | 361        | 33,21 %                            |
| Asera Permai    | 234        | 21,53 %                            |
| Grand Asera     | 154        | 14,17 %                            |
| Bukit Asera     | 102        | 9,38 %                             |
| Asera Regency   | 63         | 5,8 %                              |
| Griya Asera     | 42         | 3,68 %                             |
| Asera Garden    | 36         | 3,31 %                             |
| Asera Residence | 33         | 3,04 %                             |
| Pondok Asera    | 28         | 2,58 %                             |

Based on sales data from PT. Asera Properti, Pondok Harapan is the housing complex with the largest contribution to total sales, recording 361 transactions (33.21%). Its popularity is influenced by its strategic location, adequate facilities, and competitive prices. In second place, Asera Permai recorded 234 transactions (21.53%), followed by Grand Asera with 154 transactions (14.17%), demonstrating significant appeal in the market with growth opportunities through more effective marketing strategies.

In the moderate category, Bukit Asera recorded 102 transactions (9.38%), while Asera Regency with 63 transactions (5.8%) and Griya Asera with 42 transactions (3.86%) showed promising contributions if supported by more relevant promotions and facility development. In the low category, Asera Garden recorded 36 transactions (3.31%), Asera Residence recorded 33 transactions (3.04%), and Pondok Asera recorded 28 transactions (2.58%), requiring evaluation to improve competitiveness through product feature analysis and marketing strategies. The housing complex with the lowest contribution, Asera Griya Harapan, only recorded 10 transactions (0.92%) and requires a comprehensive approach in the form of service development, more effective marketing campaigns, and attractive offers to increase its appeal.

The strategic focus should be on maintaining the competitive advantage of Pondok Harapan and Asera Permai, developing market potential in Grand Asera and Bukit Asera, and increasing the attractiveness of low-contribution housing through discounts, payment flexibility, or additional facilities. With the right approach, the company can increase competitiveness and optimize sales in all segments.

#### b. Sales Description Based on Payment Bank

Banks are strategic partners in the property business, especially in the payment and financing processes. Sales analysis based on the banks used by customers provides an overview of customer preferences and helps PT. Asera Properti evaluate its cooperation with banks, identify preferred banks, and design relevant marketing strategies.

**Table 3.** Bank Dominance in Customer Transactions

| Bank            | Total Data | Proportion of Data in Each Cluster |
|-----------------|------------|------------------------------------|
| BRI Maros       | 258        | 23,76 %                            |
| BRI Panakukang  | 240        | 22,1 %                             |
| BTN Panakukang  | 126        | 11,6 %                             |
| BTN Gowa        | 100        | 9,21 %                             |
| BTNS Panakukang | 77         | 7,09 %                             |
| BTN Maros       | 48         | 4,42 %                             |
| BTNS Makassar   | 43         | 3,96 %                             |
| CASH            | 40         | 3,68 %                             |
| BTN Makassar    | 31         | 2,85 %                             |
| BNI             | 29         | 2,67 %                             |
| BTN Antang      | 25         | 2,3 %                              |
| BSI             | 16         | 1,47 %                             |
| BTN Alauddin    | 9          | 0,63 %                             |

BRI Maros and BRI Panakukang dominated transactions, with a collective contribution of nearly half of the total, recording 23.76% and 22.1% respectively. This dominance reflects customer trust and the effectiveness of their marketing strategies. In the medium category, BTN Panakukang (11.6%) and BTN Gowa (9.21%) play an important role, especially in property financing, but still have opportunities to increase competitiveness through service innovation.

Meanwhile, BSI (1.47%) and BTN Alauddin (0.63%) are in the low contribution category, requiring more intensive promotion to attract more customers. Non-dominant banks such as BTN Gowa and BRI Makassar show small contributions and are advised to focus on relevant local

services and targeted promotional strategies. This analysis underscores the importance of optimizing each bank's strategy to increase their contribution to banking transactions.

#### c. Sales Description Based on Communication Media

Communication media play an important role in interactions between companies and customers. In property sales, effective media can enhance the customer experience, speed up transactions, and strengthen the company's relationship with consumers. This analysis examines customer preferences for the communication media used, namely WhatsApp, telephone, and other methods.

**Table 4.** Dominance of Communication Media in Customer Interactions

| Communication Media | Total Data | Proportion of Data in Each Cluster |
|---------------------|------------|------------------------------------|
| WhatsApp            | 371        | 34,1 %                             |
| Telepon             | 367        | 33,73 %                            |
| Email               | 350        | 32,17 %                            |

### Data Dashboard Creation

A dashboard is a visualization tool designed to present analysis results interactively and in an easy-to-understand manner. In this study, the dashboard is used to illustrate clustering results, descriptive analysis, and data distribution based on categories such as housing type, communication media, and payment banks.

#### a. Data Preparation

The analysis results were consolidated and processed to ensure completeness and consistency. Relevant columns, such as Cluster, Housing Type, Payment Bank, and Communication Method, were arranged to support visualization.

#### b. Dashboard Creation Tools

The selection of tools in this study aimed to support effective and efficient data analysis. Data is imported from Excel files to Google Colab, uploaded using the upload feature, and then read with the panda's library to ensure the data structure is correct. Data is prepared by selecting relevant variables and, if necessary, standardized using StandardScaler. The K-Means algorithm is applied to group data based on interaction frequency and transaction duration, resulting in 8 clusters with different characteristics.

The analyzed dataset is exported to an Excel file in comma separated values (CSV) format and imported into Power Business Intelligence using the Get Data feature. The data is cleaned using Power Query Editor, then visualized with graphs such as donut charts for cluster distribution, housing sales, payment banks, and customer communication methods. The dashboard was enhanced with interactive visual elements such as filters based on clusters, housing, or banks, and could be published to Power BI to share with the team. This process provided a complete flow from data processing to visualization that was ready to support decision making.

#### c. Visualization Creation

In data analysis, various visualizations are used to provide clear insights. "Cluster Distribution" is visualized with a Donut Chart, showing the proportion of customers in each cluster to facilitate understanding of customer distribution. "Payment Banks" are also displayed with a Donut Chart, illustrating the contribution of each bank to total transactions and providing perspective on the dominance of banks in payments. In addition, "Communication Media" is visualized with a Donut Chart, showing communication methods such as WhatsApp and Telephone used by customers. Finally, "Type of Housing" displays the distribution of sales based on housing through a Donut Chart, providing an overview of market segmentation based on the type of property purchased. This combination of visualizations facilitates data analysis from various perspectives.

## Functional Testing

**Table 5.** Dashboard Functional Testing

| No | Features Tested                      | Input                                       | Expected Output                                                   | Test Results | Status  |
|----|--------------------------------------|---------------------------------------------|-------------------------------------------------------------------|--------------|---------|
| 1  | Donut Chart for Cluster Distribution | Clustering results dataset                  | The graph shows the corresponding cluster distribution            | As is        | Success |
| 2  | Donut Chart for Communication Media  | Customer communication method data          | The chart shows customer communication method preferences         | As is        | Success |
| 3  | Donut Chart for Bank                 | Transaction data by bank                    | The graph shows the distribution of transactions by bank          | As is        | Success |
| 4  | Donut Chart for Housing              | Transaction data based on housing           | The graph shows the distribution of transactions based on housing | As is        | Success |
| 5  | Filter for Cluster                   | Dataset clustering                          | Filters enable data selection based on clusters                   | As is        | Success |
| 6  | Filter for Communication Media       | Customer Communication Data                 | Filters enable data selection based on method                     | As is        | Success |
| 7  | Data Integration                     | Clustering results and transaction datasets | Integrated data with appropriate visualization                    | As is        | Success |
| 8  | Dashboard Layout                     | All visualization elements                  | The dashboard layout is neat and easy to understand               | As is        | Success |

Based on the results of the dashboard functionality test, visualizations such as Donut Charts for cluster distribution, customer communication methods, bank transactions, and housing successfully displayed accurate graphs in accordance with the input dataset. In addition, the filter features for clusters and communication media also work well, allowing users to filter data specifically according to their needs. The integration of clustering results with transaction data proved to work well, producing integrated visualizations. The dashboard layout also meets the criteria of being neat and easy to understand, enabling it to convey information effectively.

## Design Validation Testing

This test was conducted using a questionnaire to evaluate the usefulness of the information dashboard design that had been developed. The questionnaire was designed to measure the extent to which the dashboard met user needs in terms of functionality, ease of access, and effectiveness of information delivery. Respondents in this test consisted of individuals with strategic roles in the company, namely company directors, general managers who manage overall operations, and staff coordinators from the finance and accounting departments who understand corporate financial management. Their participation ensured that the test covered a variety of perspectives, resulting in a comprehensive evaluation.

**Table 6.** Respondent Profile

| No | Position           | Experience | Interest                                                                                                   |
|----|--------------------|------------|------------------------------------------------------------------------------------------------------------|
| 1  | Director           | 8 Years    | As an owner, knowing comprehensive information about the company's business condition for decision making. |
| 2  | General Head       | 2 Years    | As an operational manager, knowing sales activities and sales achievement.                                 |
| 3  | Coordinating Staff | 2 Years    | As a finance and accounting coordinator staff, for information on profits and finances.                    |

The results of this evaluation process are contributions from experts or individuals who hold strategic positions in the company. This evaluation provides in-depth insights into the effectiveness of the dashboard design. The following are the results of the evaluation conducted by these experts or key personnel:

**Table 7.** Usability Testing Results

| Question Code | Question Average Score | Indicator average score total |
|---------------|------------------------|-------------------------------|
| A1            | 4,33                   |                               |
| A2            | 4,33                   | 4,22                          |
| A3            | 4                      |                               |
| B1            | 4,67                   | 4,17                          |
| B2            | 3,67                   |                               |
| C1            | 4                      | 4,35                          |
| C2            | 4,67                   |                               |
| D1            | 4                      | 4                             |
| E1            | 4,33                   |                               |
| E2            | 3,67                   | 4,16                          |

The usability testing results show that the dashboard design has a fairly good level of usability. The Learnability indicator scored 4.22, indicating that users find it easy to learn the system. The Memorability indicator scored 4.17, indicating that users can remember how to use it well. Efficiency scored the highest, at 4.35, reflecting the effectiveness of using the dashboard. Meanwhile, the Errors indicator scored 4.00, indicating minimal errors in use. Finally, the Satisfaction indicator scored 4.16, indicating user satisfaction with the design.

## CONCLUSIONS

Based on research on property consumer behavior analysis, this study successfully designed business intelligence by integrating customer data from customer relationship management as the basis for analysis. Machine learning algorithms, specifically K-Means Clustering, were used to provide strategic insights, enabling the company to design strategies to attract new consumers, especially in clusters with high presentation rates. Data visualization through interactive dashboards using Power business intelligence provided a comprehensive view of consumer behavior patterns, product preferences, and transaction trends. The implementation of this business intelligence has proven effective in analyzing consumer behavior, designing loyalty programs, improving operational efficiency, and prioritizing customer clusters that make a significant contribution. The evaluation

shows that the developed dashboard is effective in managing customer data and providing relevant insights to support strategic decision-making.

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