

Article

Basic Application of Business Intelligence in making E-Commerce Buyer Dashboard Indonesian Using Tableau Tools Development

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Abstract: This research examines the implementation of Business Intelligence (BI) for the creation of an Indonesian e-commerce buyer dashboard in 2024 with the aim of increasing the visibility of operational KPI and demonstrating a reproducible pipeline from data cleaning to visualization. The main issues addressed are the quality of order-level data (provincial writing variants, date format, numerical values, and PII anonymization) as well as the need to calculate buyer metrics (unique buyers, repeat rate) which is rarely available in public aggregate data. The methods used include: (1) data cleaning and harmonizing using OpenRefine; (2) numerical transformation and validation with Python (pandas); (3) creating interactive worksheets and dashboards in Tableau (sales map per province; monthly trend line; bar with avg sales per product; sales pie by gender); and (4) sensitivity analysis to assess the impact of cleaning step variation on buyer-level KPI. Using the order-level dataset of cleaning results (1,000 transactions), a total revenue of Rp 2,298,975,000, 1,000 orders, and 178 unique buyers were found; seasonal patterns were seen with a peak in the fourth quarter and revenue concentration in urban areas (DKI Jakarta, West Java). The top-10 products contribute a significant portion of revenue, and repeat buyers show an important role in the sales structure

Keywords: Business Intelligence; Dashboard; Data Science; E-Commerce; OpenRefine; Tableau

1. Introduction

The development of the digital economy in Indonesia over the past decade has driven rapid growth in the e-commerce sector. The adoption of marketplace platforms and online sales channels by micro, small, and medium enterprises (MSMEs) and large retailers has created a vast and heterogeneous flow of transaction data [1]. If the data is processed and analyzed properly, it will have great potential to support faster and evidence-based business decision making (data-driven decision making) [2]. However, in practice, many business actors have not utilized their transaction data optimally due to limited technical capabilities, data integration barriers, and a lack of adequate analytical infrastructure [3].

Business Intelligence (BI) has emerged as a framework and toolkit for transforming raw data into useful information [4]. Through ETL (Extract-Transform-Load) stages, data cleansing, business metric aggregation, and interactive visualization, BI facilitates stakeholders in observing trends, identifying anomalies, and formulating operational policies and marketing strategies [5]. Tableau, as a leading data visualization platform, provides interactive dashboard creation capabilities that make

it easy for non-technical users to explore data and monitor key performance indicators (KPIs) in real time or periodically.

In the context of e-commerce, some crucial KPIs include total revenue, number of unique buyers, sales trends per period, performance per product, and buyer demographic segmentation. Analysis of these KPIs helps management determine inventory strategies, promotions, marketing channels, and customer retention activities [6]. Furthermore, a regional (province/city) sales distribution map allows for prioritization of logistics and market expansion. While the benefits are clear, a key challenge often faced is data quality: inconsistent date formats, location typos, numeric values mixed with text, and duplicate rows require rigorous data cleaning before integration into the BI pipeline [7].

E-commerce in Indonesia is growing rapidly and generating large transaction volumes. Processing transaction data into easily understandable information is key for businesses to make operational and strategic decisions [8]. Business Intelligence (BI) provides methods and tools to transform raw data into actionable insights. This study implements a BI pipeline (ETL → cleansing → aggregation → visualization) to create an e-commerce buyer dashboard using Tableau with transaction datasets (cleaning results) available using OpenRefine.

This research has several objectives. First, to design and document a reproducible Business Intelligence workflow for 2024 order-level transaction data, from extraction to cleansing using OpenRefine and standardized transformations and aggregations. Second, to generate a clean and documented dataset and build an interactive buyer dashboard in Tableau that displays key KPIs such as revenue, number of unique buyers, sales trends per period, product performance, and geographic distribution in an easy-to-understand interface. Third, to validate the metrics and transformation logic with Python/pandas scripts to ensure the analysis results are accurate and repeatable. Fourth, to assess the usefulness of this dashboard for operational and strategic decision-making and to preserve all research artifacts such as the clean dataset, scripts, and workbooks for auditability and replication.

2. Literature Review

Research on Business Intelligence (BI) implementation in Indonesia over the past few years has shown a shift from conceptual studies to practical implementation studies that emphasize the end-to-end pipeline: from ETL and data cleaning to dashboard deployment for business decision-making [9], [10]. Several local case studies illustrate BI adoption at an organizational scale, including retail and service organizations, focusing on improving performance visibility and operational efficiency through interactive visualizations [11]. Thus, much of this work is in the form of case studies of single organizations and does not always test generalizations to the highly dynamic context of e-commerce [12]. Furthermore, local technical education literature and software engineering articles feature a variety of dashboard designs (using Tableau, Power BI, Pentaho, etc.) for various domains. However, the technical approaches presented often focus on visualization and interface aspects, with limited discussion of data cleansing and pipeline reproducibility in most practice reports [3], [13].

In the realm of e-commerce and customer analytics, several empirical studies in Indonesia have examined the relationship between digital service quality, marketing, and repurchase/loyalty behavior [14]. Showing that user experience and e-service quality metrics contribute significantly to repurchase intentions. These findings underscore the value of buyer-level analytics for retention strategies [15]. Additionally, research examining BI in supply chain/e-logistics demonstrates the benefits of BI for inventory optimization and operational decision-making, but most empirical examples use aggregate or single-company data rather than buyer-level transaction datasets, which would allow simultaneous calculation of unique buyers, repeat rates, and geospatial analysis [16].

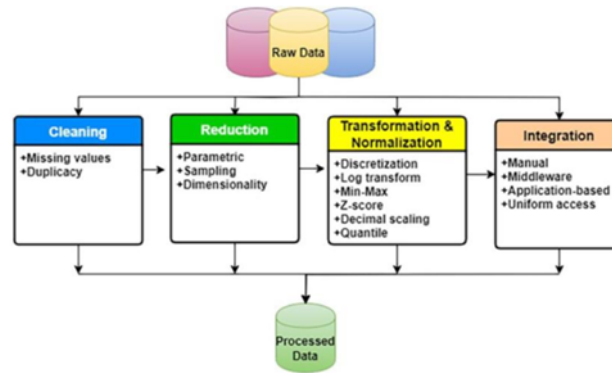


Figure 1. Data preprocessing steps and activities

As shown in Figure 1, explains more specifically about methodology and tooling. There is a tendency for local publications to discuss the use of popular BI tools (Tableau, Power BI) and simple ETL pipelines (Excel/script) to prepare data for dashboards; however, detailed documentation on the use of reconciliation-based cleansing tools (e.g., OpenRefine), clustering strategies for location standardization (provinces/districts), and anonymization practices for PII are rarely a primary focus in published articles. These steps are crucial when processing real e-commerce transaction data for publication and application in studies [3], [17]. Additionally, studies that produce dashboards tend to showcase visuals and organizational benefits (use cases), but rarely evaluate the validity of buyer-level metrics when data has quality issues (e.g., missing buyer_id, inconsistent province names), or demonstrate how consistent cleansing can impact KPI outcomes (e.g., number of unique buyers per month). This methodological gap indicates the need for studies that combine systematic cleansing practices with measurable dashboard analysis. [18], [19].

Based on this literature review, several research gaps can be clearly identified. First, few studies present a complete pipeline from transaction data cleansing (using standardized tools like OpenRefine) to deploying interactive dashboards in Tableau specifically for buyer analysis (rather than simply aggregate sales performance) [20]. Second, there is a lack of studies that utilize order-level data containing buyer_id to calculate critical indicators such as unique buyers, repeat buyer rate, and cross-tab analytics (e.g., revenue per buyer per province) while also evaluating how sensitive these KPIs are to variations in data cleansing. Third, most local publications focus on case studies of single organizations or non-e-commerce domains (e.g., hospitals, zakat, manufacturing), so generalization to national e-commerce ecosystems (with heterogeneity in platforms and buyer demographics) is still limited [1], [21].

3. Materials and Methods

3.1 Research Methodology

As shown in Figure 2, presents a detailed methodology in the form of a flowchart to facilitate understanding of the process and to guide the author to results and conclusions that align with the research objectives. This research uses a quantitative descriptive approach and an implementation study documenting the entire Business Intelligence (BI) pipeline for creating an e-commerce buyer dashboard using Tableau.

The methodology is designed following the data workflow in Figure 1, which includes a series of activities from literature review to data/dashboard publication. This approach emphasizes reproducibility and auditability: each stage (ETL, cleansing, transformation, visualization) is recorded so the process can be replicated. Conducting research requires a series of data processing steps, from literature review to storing and sharing data through Tableau Public.

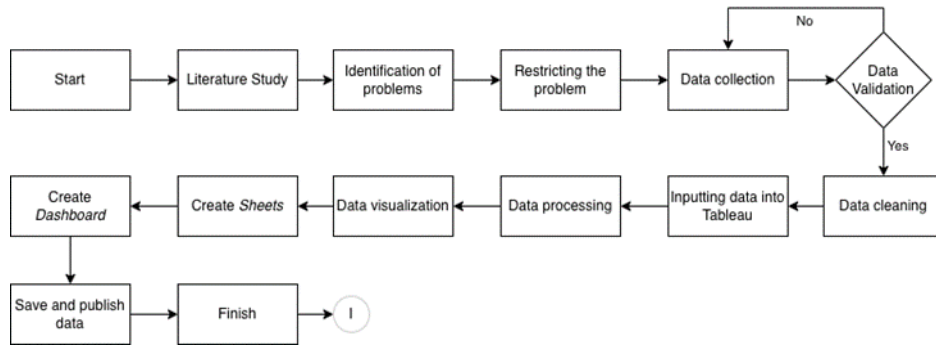


Figure 2. Flowchart of Research Stages

As shown in Figure 2, presents the overall research flowchart. The study begins with defining analytical objectives and selecting KPIs; next, secondary order-level datasets are collected and verified for provenance. Data cleaning is performed using OpenRefine to standardize date formats, harmonize province names, and anonymize PII. The cleaned dataset is exported and further transformed (derived metrics such as unique buyers and repeat rate) using Python/pandas. Final visualizations and interactive worksheets are developed in Tableau and combined into a dashboard, which is then evaluated through a sensitivity analysis that tests how different cleaning strategies affect buyer-level KPIs.

3.2 Scope of Research

The research object is order-level transaction records listed in the available dataset. The scope is limited to analysis of buyer metrics (unique buyers, repeat rate), aggregate revenue per month, per province, and per product, as well as segmentation by gender and platform [22]. The study does not include analysis of external market prices or logistics data beyond the available Province column.

3.3 Data Collection Technique

As seen in Figure 1, the raw data and the locations where the data were obtained are illustrated. The database, which may be stored on a local hard drive or a remote server, serves as the primary data source for a database management system [23], [24]. The computer program can use files, datasheets, spreadsheets, XML files, or even data encoded into the program itself as its data source [25]. Data sources generally fall into two types: primary sources and secondary sources, depending on how the data is collected or generated, as shown in Figure 3.

A computer program can use files, datasheets, spreadsheets, XML files, or even data embedded within the program itself as its data source. Data sources are generally classified into two types: Primary and Secondary depending on how the data are collected or generated, as shown in Figure 3.

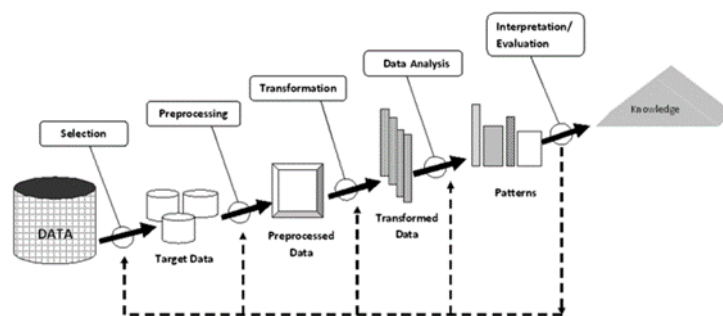


Figure 3. Transition from Primary Data to Secondary Data

As shown in Figure 3, First-hand data is generated directly by the data source and stored without any modification or preprocessing. This data can also be called original data or raw data. Collecting original, first-hand data increases the reliability and authenticity of the data [26]. Primary data

sources help uncover hidden and new facts. Generating primary data is expensive and time-consuming. Once analyzed, primary data can be further processed to produce secondary data [27].

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Because the data the author created is secondary data, collection techniques include: requesting/transferring files from data owners, verifying metadata (columns, date ranges, coding schemes), and recording provenance. If the source comes from multiple files, column consolidation and harmonization are performed before cleaning, as shown in Figure 3.

3.4 Data Analysis Techniques

The analysis was conducted in a quantitative descriptive manner: time series aggregation, product ranking based on total revenue, calculation of unique buyers and repeat rates, and geospatial visualization [3], [30]. To test the robustness of the cleanup pipeline, a sensitivity analysis was performed: experimenting with varying clustering methods in the Province column (e.g., aggressive clustering vs. conservative clustering) and observing their impact on unique buyers and revenue per province [31]. A comparison of pre- and post-cleanup results is shown in a summary table (delta KPI values) to show how much each cleanup step impacts the outcome. If necessary, simple statistical tests (e.g., paired difference tests) can be used to evaluate the significance of KPI differences between cleanup scenarios.

Table 1. Main Materials and Tools

| Software / Hardware | Version | Main Function |
|-----------------------------------|-------------------------|--|
| OpenRefine (Data Cleaning) | 3.9.5 | Initial data cleaning and standardization |
| Tableau Desktop (Data Reduction) | 2025 | Data Reduction and Visualization |
| R (Data Normalization) | 4.3.2 | Data analysis and transformation using tidyverse package |
| Tableau Public (Data Integration) | 2025 | Interactive data visualization publication |
| MacBook Pro M1 (Hardware) | macOS 15.3, RAM 8 GB | The main hardware for computing and analysis |

Based on the details of the materials and tools used in the study are presented in Table 1. Initial data cleaning was performed using OpenRefine (version 3.9.5). Data analysis and transformation were performed using R (version 4.3.2) with the tidyverse package (including dplyr) for data manipulation and statistical analysis. Data visualization and reduction were performed with Tableau Desktop (version 2025), and interactive visual results were published using Tableau Public. All procedures involving random numbers were run after setting the seed `set.seed(12345)` so that the experimental results could be reproduced. Full versions of R packages and environment information (`sessionInfo()`), as well as analysis scripts are available in the Appendix and/or code repository (see Appendix / Repository) for reproducibility purposes.

4. Results

A literature study aims to identify a problem and seek appropriate and relevant information related to the research topic in references or journals on the relevant topic. The relevant references collected must be in accordance with the method being discussed, namely Business Intelligence. Business Intelligence (BI) is defined as a decision-making process supported by the

interconnectedness and analysis of data sources. Business Intelligence (BI) presents a unique challenge in the Industrial Revolution 4.0 [32].

Literature review is crucial after a researcher has established a topic. The next step is to review various literature sources related to that particular topic. At this stage, researchers must gather as much information as possible. This information can be obtained from journals, books, previous research results, and the results of previous studies.

4.1. Data Process

The data collected is childbirth data sourced from the Mendeley dataset from January 1, 2024, to December 28, 2024. The data consists of product category data that conducted transactions in several provinces in Indonesia. Figure 4 shows E-Commerce Repeat Buyer Data in Indonesia in 2024.

| No | Tp | Data | Ctrl_ID | Age | Gender | Country | Previsni | AREA | Product | Product_Hair | Category | Amount | per_item | %_total | Noitems_per | Harga_per | Harga_total |
|----|------------|-----------|---------|-----------|-----------|--------------------------|-------------------------------|-------------------------|---------|--------------|------------------------|----------|----------|-----------|-------------|-----------|---------------|
| 1 | 01/01/2024 | CTRD00043 | 49 | Laki-laki | Indonesia | Aceh | HP-PV15 | Laipoo HP Computer | 1 | 14500000 | Electronics and Gadget | 14500000 | 14500000 | 14.500000 | 1 | 14500000 | Rp 14.500.000 |
| 2 | 02/02/2024 | CTRD00046 | 18 | Perempuan | Indonesia | Jawa Barat Bandung | 93021232 | Hair Mask (Hair Treatm | 1 | 1500000 | Cosmetics | 1500000 | 1500000 | 0.150000 | 1 | 1500000 | Rp 1.500.000 |
| 3 | 03/03/2024 | CTRD00055 | 42 | Perempuan | Indonesia | Kalimantan Banjarmasin | 93021232 | Hair Mask (Hair Treatm | 7 | 1500000 | Cosmetics | 10500000 | 10500000 | 0.105000 | 7 | 1500000 | Rp 1.500.000 |
| 4 | 04/04/2024 | CTRD00056 | 42 | Laki-laki | Indonesia | Kepulauan Batam | HE-KALLA-RT-Raku II Home Appl | | 5 | 8500000 | Electronics and Gadget | 42500000 | 42500000 | 4.250000 | 5 | 8500000 | Rp 8.500.000 |
| 5 | 05/05/2024 | CTRD00056 | 39 | Perempuan | Indonesia | Jawa Barat Cirebon | 93245275 | Perfume Of Cosmetics | 1 | 4500000 | Cosmetics | 4500000 | 4500000 | 0.450000 | 1 | 4500000 | Rp 450.000 |
| 6 | 06/06/2024 | CTRD00046 | 26 | Laki-laki | Indonesia | DKI Jakarta Jakarta | TUP-SET10 | Set Peralat Kitchen App | 1 | 3500000 | Electronics and Gadget | 3500000 | 3500000 | 0.350000 | 1 | 3500000 | Rp 350.000 |
| 7 | 07/07/2024 | CTRD00056 | 40 | Perempuan | Indonesia | Jawa Timur Kediri | 81932012 | Bhush ZAB Cosmetics | 1 | 2500000 | Cosmetics | 2500000 | 2500000 | 0.250000 | 1 | 2500000 | Rp 250.000 |
| 8 | 08/08/2024 | CTRD00047 | 54 | Perempuan | Indonesia | Jawa Timur Malang | 55171815 | Makleup Re Cosmetics | 3 | 2500000 | Cosmetics | 7500000 | 7500000 | 0.750000 | 3 | 2500000 | Rp 250.000 |
| 9 | 09/09/2024 | CTRD00056 | 24 | Laki-laki | Indonesia | Sulawesi U Marado | 5AM-060T | Televiz Sar Electronics | 1 | 6850000 | Electronics and Gadget | 6850000 | 6850000 | 6.850000 | 1 | 6850000 | Rp 6.850.000 |
| 10 | 10/10/2024 | CTRD00053 | 47 | Laki-laki | Indonesia | Nusa Tenggara | XIA-MIRV | Vacuum Ck Electronics | 1 | 3599000 | Electronics and Gadget | 3599000 | 3599000 | 3.599000 | 1 | 3599000 | Rp 3.599.000 |
| 11 | 11/11/2024 | CTRD00051 | 18 | Perempuan | Indonesia | Sumatera I Medan | 23242575 | Perfume Of Cosmetics | 1 | 4500000 | Cosmetics | 4500000 | 4500000 | 0.450000 | 1 | 4500000 | Rp 450.000 |
| 12 | 12/12/2024 | CTRD00057 | 35 | Perempuan | Indonesia | Sumatera I Padang | 01112123 | Body Scrub Body Treat | 2 | 3000000 | Cosmetics | 6000000 | 6000000 | 0.600000 | 2 | 3000000 | Rp 3.000.000 |
| 13 | 01/13/2024 | CTRD00043 | 21 | Laki-laki | Indonesia | Jawa Tengah Semarang | BRK-MRAD | Jam Tangan Convienco | 1 | 3500000 | Electronics and Gadget | 3500000 | 3500000 | 3.500000 | 1 | 3500000 | Rp 3.500.000 |
| 14 | 02/14/2024 | CTRD00041 | 40 | Perempuan | Indonesia | Riau Pekanbaru | 24252686 | Whitening Cosmetics | 1 | 2500000 | Cosmetics | 2500000 | 2500000 | 0.250000 | 1 | 2500000 | Rp 250.000 |
| 15 | 03/15/2024 | CTRD00046 | 51 | Perempuan | Indonesia | Banten Tangerang | 93021223 | Eye Cream Cosmetics | 2 | 2500000 | Cosmetics | 5000000 | 5000000 | 0.500000 | 2 | 2500000 | Rp 250.000 |
| 16 | 04/16/2024 | CTRD00055 | 36 | Perempuan | Indonesia | DI Yogyakarta Yogyakarta | 93445667 | Body Lotion Body Treat | 3 | 3000000 | Cosmetics | 9000000 | 9000000 | 0.900000 | 3 | 3000000 | Rp 300.000 |
| 17 | 05/17/2024 | CTRD00041 | 38 | Perempuan | Indonesia | Jawa Tengah Purwokerto | 94556678 | Hair Serum Hair Treatm | 1 | 1500000 | Cosmetics | 1500000 | 1500000 | 0.150000 | 1 | 1500000 | Rp 150.000 |
| 18 | 06/18/2024 | CTRD00043 | 49 | Laki-laki | Indonesia | Bali Aceh | HEI-8PRD | Smartphon Electronics | 1 | 4650000 | Electronics and Gadget | 4650000 | 4650000 | 4.650000 | 1 | 4650000 | Rp 4.650.000 |
| 19 | 07/19/2024 | CTRD00046 | 18 | Perempuan | Indonesia | Jawa Barat Bandung | 55171815 | Makleup Re Cosmetics | 1 | 2500000 | Cosmetics | 2500000 | 2500000 | 0.250000 | 1 | 2500000 | Rp 250.000 |
| 20 | 08/20/2024 | CTRD00055 | 42 | Perempuan | Indonesia | Sulawesi Sa Banjarmasin | 94556678 | Hair Serum Hair Treatm | 5 | 1500000 | Cosmetics | 7500000 | 7500000 | 0.750000 | 5 | 1500000 | Rp 150.000 |
| 21 | 09/21/2024 | CTRD00058 | 27 | Perempuan | Indonesia | Kalimantan Batam | 90212242 | Deodorant Cosmetics | 1 | 2500000 | Cosmetics | 2500000 | 2500000 | 0.250000 | 1 | 2500000 | Rp 250.000 |
| 22 | 10/22/2024 | CTRD00056 | 40 | Perempuan | Indonesia | Kalimantan Cirebon | 778899001 | Shampoo V Hair Treatm | 3 | 1500000 | Cosmetics | 4500000 | 4500000 | 0.450000 | 3 | 1500000 | Rp 150.000 |
| 23 | 11/23/2024 | CTRD00046 | 26 | Laki-laki | Indonesia | Kalimantan Jakarta | PCL-165 | Sepeda Pol Sport | 2 | 8000000 | Electronics and Gadget | 16000000 | 16000000 | 16.000000 | 2 | 8000000 | Rp 8.000.000 |
| 24 | 12/24/2024 | CTRD00056 | 40 | Perempuan | Indonesia | Jawa Timur Kediri | 22334264 | Acne Gel Lf Cosmetics | 6 | 2500000 | Cosmetics | 15000000 | 15000000 | 1.500000 | 6 | 2500000 | Rp 250.000 |
| 25 | 01/25/2024 | CTRD00051 | 44 | Laki-laki | Indonesia | Lampung Malang | ANK-PB10C | Power Banl Electronics | 1 | 2500000 | Electronics and Gadget | 2500000 | 2500000 | 0.250000 | 1 | 2500000 | Rp 250.000 |
| 26 | 02/26/2024 | CTRD00056 | 24 | Laki-laki | Indonesia | Jawa Timur Marado | APP-1P3 | Smartphon Electronics | 2 | 8249000 | Electronics and Gadget | 16498000 | 16498000 | 16.498000 | 2 | 8249000 | Rp 8.249.000 |
| 27 | 03/27/2024 | CTRD00054 | 48 | Perempuan | Indonesia | Jawa Barat Medan | 81932012 | Bhush ZAB Cosmetics | 1 | 2500000 | Cosmetics | 2500000 | 2500000 | 0.250000 | 1 | 2500000 | Rp 250.000 |
| 28 | 04/28/2024 | CTRD00051 | 18 | Perempuan | Indonesia | Jawa Barat Medan | 90212242 | Deodorant Cosmetics | 1 | 2500000 | Cosmetics | 2500000 | 2500000 | 0.250000 | 1 | 2500000 | Rp 250.000 |
| 29 | 05/01/2024 | CTRD00057 | 35 | Perempuan | Indonesia | Kepulauan Padang | 141516171 | Foot Cream Body Treat | 1 | 3000000 | Cosmetics | 3000000 | 3000000 | 0.300000 | 1 | 3000000 | Rp 300.000 |

Figure 4. E-Commerce Repeat Buyer Database in Indonesia 2024

The data was obtained directly from the Mendeley dataset. The data collected included 178 customers with sales totaling Rp2,298,975,000 and a profit of Rp1,312,510,000. From this data, it can be concluded that the best-selling products are Electronics and Gadgets.

Data processing is performed using Business Intelligence methods with Tableau Public software. Tableau is a software application for analyzing and visualizing data sets into information for decision-making. There are many types of Tableau, including Tableau Desktop, Tableau Prep, Tableau Online, and Tableau Public [13]. Business Intelligence itself has several benefits for companies, such as increasing the value of organizational data and information, making it easier to monitor organizational performance, making IT investments better, making it easier for employees to access information, and making costs more efficient.

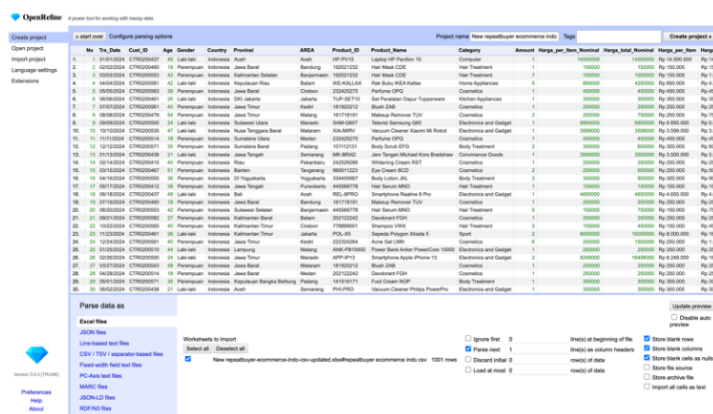


Figure 5. Cleaning Search Results in the OpenRefine Application

Next, in Figure 5 shows the data cleaning process for the dataset previously exported from the Excel database in Figure 4 and then imported into the OpenRefine application. This process includes

identifying and grouping spelling variations (e.g., "West Java", "West Java", "West Java") using clustering and faceting methods, correcting typos, removing duplicates, and normalizing category and location labels to ensure consistent entries. OpenRefine is used to interactively preview changes (before-after preview) so operators can assess and accept transformations before applying them to all columns.

Data type validation (string-to-numeric conversion in price/quantity columns) and filling/marking of missing values are also performed, where necessary. These cleaning results are important because they directly impact KPI aggregation in number of unique buyers, sales distribution by province, the product ranking by reducing noise and bias caused by inconsistent entries. To ensure reproducibility of the analysis, all changes are logged (export changelog/operations) and are recommended to be included as an attachment or repository accessible to reviewers.

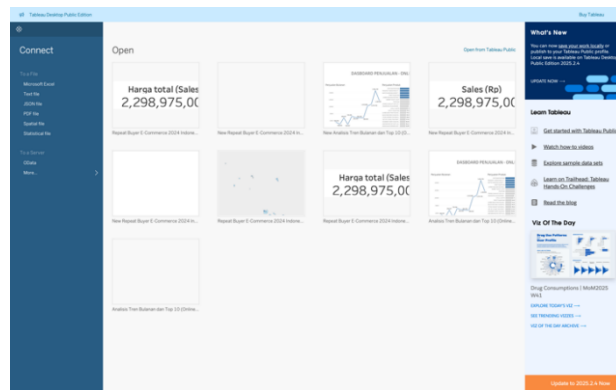


Figure 6. Initial View of the Tableau Public Application

After importing a data source into Tableau, the first view in Figure 6 shows the Connect panel on the left (*To a File Microsoft Excel option*) and an Open area where thumbnails of available workbooks and work sheets are shown. This screen will enable the preview of the data source, the name of the workbook and already created worksheets/ KPI cards (e.g., Total Price Rp 2,298,975,000) which will allow already check the number of rows and fields that will be used in visualization. The first view has buttons and contextual menus which allow rapid navigation.

To check the type of the variable (*string, numeric, date*) by open the Data Source, refresh the connection, or to go to a particular worksheet using the Go To Worksheet window. This perspective provides the basis of creating dashboards: researchers are able to peruse field mappings, pin assign right data types, organize time hierarchies, and preview sample values prior to making additional visualizations. To make the workbook reproducible and reviewable, it is suggested that the workbook should be saved as a package (*.twbx*) or published to a repository (Tableau Public / institutional repository) and a link or export file be included in the manuscript attachment.

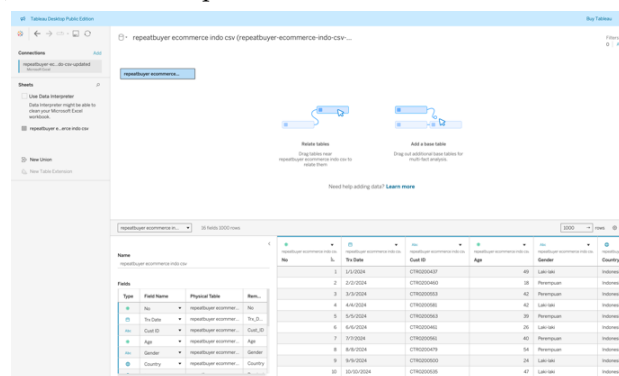


Figure 7. Pop Up Go To Worksheet

The imports are followed by making Use Data Interpreter of Tableau available in Tableau Data Source view in Figure 7. This feature helps Tableau to spot rows of mismatched headers, remedy merged cells, and delineate the types of the columns (date, text and number) to help Tableau come up with a more uniform table design before it generates visualizations.

The lowest panel shows a metadata grid which previews rows, field names and data types which helps the researcher to make quick corrections as in changing column types or deleting unneeded columns or splitting/pivoting columns. Furthermore, at this point users may create relationships or joins among sheets in case the dataset is made of several tables and formulate extracts to enhance workbook performance as well as add data-source filters to reduce the scope of analysis.

Once the data structure has been validated and corrected, the researchers will create a KPI worksheet Figure 8 that will present the key metrics, including: the number of orders, the number of unique buyers, total revenue, and the total profit, on which the whole analytics dashboard will be based. In order to reproducibly verify a transformation, all the transformation steps and settings of the Data Source are remembered or expelled (save as .twbx / export metadata) that reviewers can determine the visualization pipeline up to that point.

4.2. Data Visualization

The following are the steps for data processing to visualize it. The first step is to input the data to be processed, as shown in Figure 7. The data will be processed in the Public Tablue, as shown in Figure 7. The data visualizations used include KPIs, Sales by Month, Sales by Province, Sales by Product, and Sales by Gender, plus filters and an Interactive Dashboard.

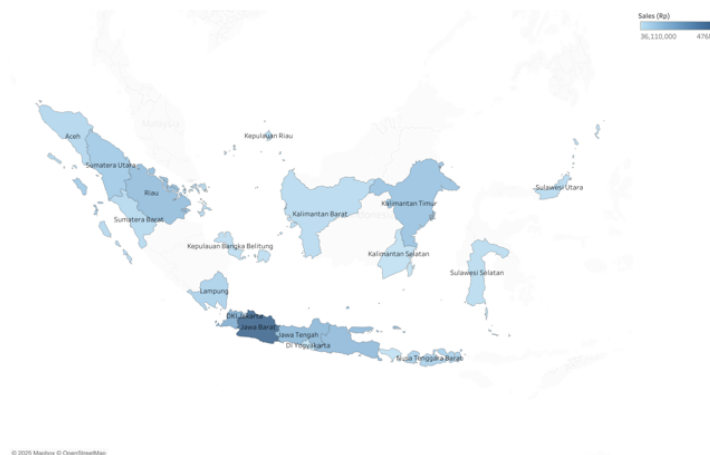


Figure 8. Sales by Province

In Figure 8 demonstrates thematic choropleth map, which shows the distribution of total retail sales of Indonesian provinces in January 1 - December 28, 2024 starting at a range of about Rp 36,110,000 to Rp 476,000,000. The graphical representation shows that sales are concentrated mainly on the island of Java with the biggest contribution of West Java at about Rp 475,808,000 and Jakarta at about Rp 221,800,000. Provinces located in the Kalimantan, and sections of Sumatra, are placed in a middle-tier opposition, and areas east such as Sulawesi and the Nusa Tenggara archipelago pattern a relatively lower level of sales. This analysis is supplemented by the interactive dashboard, which shows absolute provincial values, along with their percentage contribution during the total revenue, thus, making it easier to prioritize the high-yield provinces and then devote further investigative attention to these particular provinces.

The implications of this trend based on practice include a series of operation management procedures. Among them, the rational management of stocks, the strengthening of the specific marketing activities, and the rationalization of the logistical paths within the provinces with the best sales quotas can be identified as priority measures [33]. At the same time, there is a recommendation to re-audit segmented marketing approaches of areas with a rather underperforming performance within the field and make sure that the allocation of resources follows the localized consumer behavior and market opportunities. Following this kind of evidence-based interventions, companies

will be able to optimize the effectiveness of their supply chains, as well as the effectiveness of their market penetration prospects.

Analytically, to compare the situation between provinces, the author suggests the normalization of sales data by taking into account some variables (per-capita income, or product penetration rates per 1,000 residents) to bring the provinces to a more representative level. Also, it is suggested to have a granular drill-down by product type or sales channel, which makes it possible to understand inter-provincial differences in a subtle way. These types of methodological fine tunings will aid in comparative analysis that is stronger and strategy decisions made both at the provincial and the national levels.

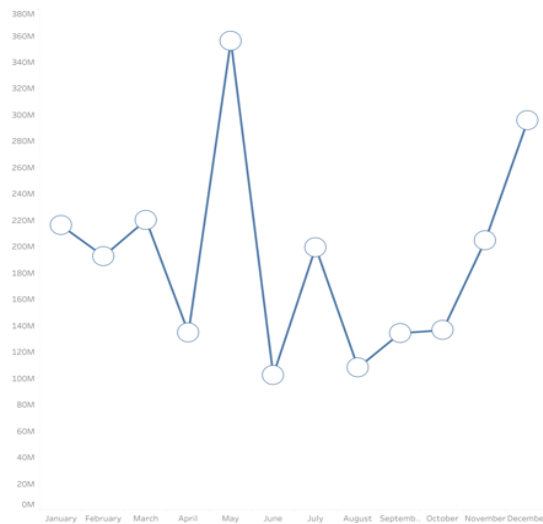


Figure 9. Sales by Month

In Figure 9 shows the trend in the monthly sales that has been seen in 2024. The same period January-March was rather stable with the results spanning between Rp 190,000,000 to Rp 220,000,000. This stability was succeeded by a significant fall back in April (around Rp 140,000,000). This dataset then shows one strong spike in May and this could be described as a seasonal outlier. Later in June, the level of sales dropped drastically (approximately Rp 105,000,000). We can see that there is a rebound in July (around Rp 195,000,000) and the sales became worse in the period of August-October, with the results ranging between Rp 110,000,000 and Rp 140,000,000. Lastly, one can see the gradual growth to the end of the year and the ultimate high at the end of December of about Rp 295,000,000.

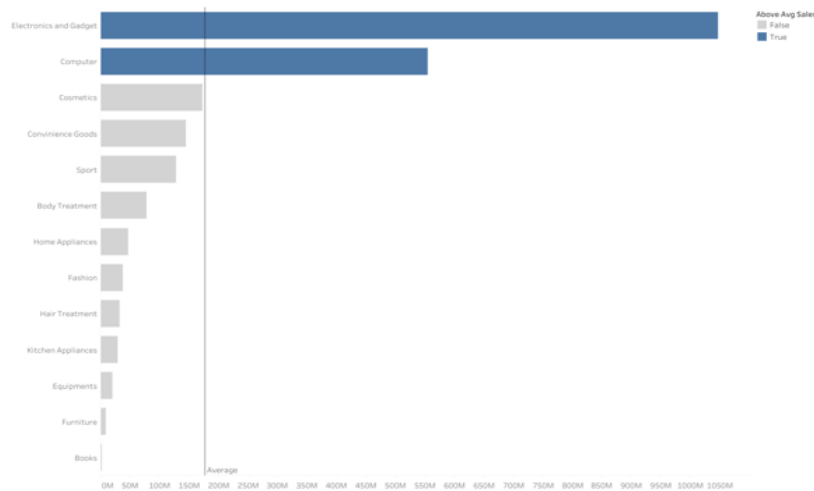


Figure 10. Sales by Product

The identified pattern can indicate the influence of a season or the presence of specific events that triggered the anomaly in May and a consistent increase to the end of the year the promotion

activities, sales holidays, shortage of inventory, or the change of the marketing channels. In order to support the underlying reasons of such fluctuations, one should consider running some correlation analysis on the time series of sales and on the records on promotional activity (dates and types) inventory/fulfilment indicators, and channel performance indicators (e.g., web traffic, conversion rates) over the same period.

Figure 10 shows the sales distribution graph per product against the average line (≈ 200 million). Electronics & Gadgets stand out far above the average (around $>Rp 1$ billion), followed by Computers which are also significantly above the average (Rp 554 million). Other products are mostly below the average: Cosmetics (Rp 172.5 million), Convenience Goods (Rp 144.5 million) and Sport (Rp 128 million) are slightly below the average, while Body Treatment, Home Appliances, Fashion, Hair/Kitchen Appliances, Equipments, Furniture, and Books show a relatively small sales contribution (range from tens of millions to very minimal).



Figure 11. Product Sales by Gender

The analysis of product sales in terms of gender, according to Figure 11, shows that in the entire sample ($n= 122$) male buyers represented the major segment which was around 85 -90 percent. On the other hand, the size of female buyers was a comparative minority because it only was about 1015 per cent. The given results highlight the finding of a high level of gender disparity in the demand of the products among the identified sample population, where male consumers and their buying habits determine the overall volume of sales.



Figure 12. Interactive Dashboard of Repeat Buyers of E-Commerce Indonesia 2024

Source: <https://public.tableau.com/app/profile/uya.syuura.anandri/viz/NewRepeatBuyerE-Commerce2024IndonesiaDataset/Dashboard1?publish=yes>

These observations have a substantive implication on the product development and the marketing strategy. First, the company should consider diversifying and refining the product attributes including product features, design, size, and packaging in order to reflect more closely female consumer preferences hence increasing product appeal to the demographic. Second, more granular marketing strategy might need to be adopted that includes targeted digital campaigns targeted at females, partnerships with female influencers or brand ambassadors, customization of messages of communication and channel of distribution in order to better address the unique needs of this segment. Thirdly, it is suggested to use the control marketing experiment, such as A/B tests,

and compare them with qualitative research tools such as focus groups or in-depth interviewing, to explain the obstacles to female buyers joining and assess the effectiveness of the potential interventions.

In Figure 12 shows the 2024 Indonesian E-commerce Buyer Dashboard that is an interactive sales analysis module that is subdivided by time interval, product, province of origin, and gender of the buyer. The graphical depiction records bar sales in the sum of Rp 2,298,975,000 of which the net profit is Rp 1,312,510,000 in 178 different customers. The peak of sales is in May when Electronics and Gadgets domain is represented as the most successful product line and the distributions of transactions are also mainly limited in Java and Sumatra. The age structure of buyers is majorly male.

The novelty of the methodology and value proposition of this question would be the application use of a Tableau-based interactive dashboard that provides real-time analytics, multi-dimensional synthesis, and emphasizing the context of the Indonesian e-commerce environment. This kind of tool complements the comprehensive interpretation of data, and forms the basis of a sensible, data-driven decision-making process.

5. Conclusions

The proposed research paper describes the calculation and monitoring of buyer key performance indicators (KPIs) in e-business scenarios based on a Business Intelligence (BI) what can be called a replicable Business Intelligence (BI) pipeline. The transactional analysis shows that there is a cumulative revenue of Rp2,298,975,000 based on 1000 orders made by 178 different buyers and that the focus point is on the Java Island region, Electronics and Gadgets category occupies the largest portion of revenue and seasonality can be clearly, that it is clearly high during the month of May and at the season when the fiscal year has ended.

The buyer profiling shows that there is a high number of male customers and the number of regular customers plays a considerable role. The methodological contributions include repeatable ETL and visualization pipeline, a workflow that is pragmatically sound and practical in extracting and authenticating buyer KPIs out of unclean data and empirical evidence of the sensitivity of KPIs values to data-cleaning choices. The study constraints include use of one single-platform, secondary data Short data with limited duration, absence of full demographic data of buyers and lack of a test of dashboard usability. We would, therefore, suggest strict reporting of the cleaning processes, strength tests, extrapolation of cross-platform dataset with and without in-depth demographics, widened usability tests and exploring possibilities of real time integration.

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