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# Enhancing handicraft exports in West Java: A business intelligence approach to market expansion

Fansuri Munawar [1], Ghifari Munawar [2,*], Didi Tarmidi [1]

[1]*Faculty of Economics and Business, Universitas Widyatama, Bandung, Indonesia*
[2]*Department of Computer Engineering and Informatics, Politeknik Negeri Bandung, Bandung, Indonesia*

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ABSTRACT

The creative industries in West Java have significantly boosted the region's economy, contributing to higher GDP, more jobs, and increased exports. However, the handicraft sector seeks to grow its presence in the international market, where it currently holds a minor share. To address the challenges of expanding, such as limited information, marketing obstacles, and regulatory hurdles, the handicraft industry is encouraged to adopt a business intelligence (BI) platform. This study aims to use a BI platform to present and analyze export data for West Java's craft industry, examining its distribution, trends, and future prospects to help increase exports from this Indonesian province. The analysis employs clustering with k-means, time series analysis, and forecasting methods, including exponential smoothing and the compound annual growth rate (CAGR), using export data from 2018 to 2022. The process involves collecting primary and secondary data, transforming it through ETL (Extract, Transform, Load) technology, and integrating it into the BI platform for analysis. This analysis aims to identify export patterns, trends, and make forecasts that can guide decision-making. The findings indicate that handicraft exports are categorized into three destination country clusters, each favoring different product types, revealing trends and growth opportunities for various handicraft items. Additionally, the study provides forecasts for handicraft exports, offering valuable insights for strategic planning.



## 1. Introduction

The creative industries have become one of the most critical sectors in the modern economic system. This industry has developed rapidly and significantly drives economic growth and social prosperity in various countries, including Indonesia (Munawar et al., 2022). The creative industries promote both economic and social well-being by creating jobs and increasing living standards (Putra et al., 2022). While the creative industries promise a better economy, their impact on future development remains uncertain (Saleh, 2022). Despite their continued importance to Indonesia's economic landscape, the contribution of creative industries to GDP shows a downward trend. This development, characterized by a decline from IDR 1,153.4 trillion (7.3%) in 2019 to IDR 1,134 trillion (6.98%) in 2021, requires increased efforts to ensure the growth and sustainability of this important to promote the sector.

Despite its considerable potential, Indonesia still needs to improve its export performance of handicraft products. The main challenge is limited export competitiveness and the inability to compete with other countries in the global market. For example, handicraft exports contribute only 1.09% globally, while countries such as China, Japan, and Vietnam have a much higher share. For example, China's export contribution is 8.1%, while Indonesia's is only 1.09% (FHAN, 2015). In addition, there are internal and external barriers to global expansion, including information constraints, marketing challenges, procedural complexities, regulatory requirements, and environmental policies (Munawar et al., 2019).

The craft industry faces several challenges while adapting to rapid changes in market dynamics, environmental factors, and technological advances. Encouraging creative innovation in product development is also proving to be difficult.

* Corresponding Author.
Email Address: ghifari.munawar@polban.ac.id (G. Munawar)
https://doi.org/10.21833/ijaas.2024.03.022
Corresponding author's ORCID profile:
https://orcid.org/0000-0001-5277-1411

Therefore, the industry needs to focus on improving the utilization of market opportunities, maximizing available resources, and managing risks associated with entering new markets. Information technology plays a crucial role in overcoming these challenges to increase handicraft product exports. One approach is to use a business intelligence platform that retrieves and analyzes business information for better decision-making (Munawar and Munawar, 2023).

Business intelligence (BI) platform use historical data to estimate potential export time for years by analyzing export performance data. Data sources include the Indonesian Ministry of Industry and Trade, the Central Statistics Agency, relevant government regulations or policies, interviews and field surveys with craft business actors, and secondary data from external sources. Therefore, an in-depth analysis of export patterns in Indonesia's creative handicraft sector through information technology is necessary to increase the export of handicraft products. Such an analysis can provide insight to business actors regarding craft products that compete in the global market and help them identify potential opportunities. In this context, information technology solutions such as BI platforms become relevant tools that provide direction and valuable information for analyzing product exports (Neubert and Van der Krogt, 2018).

BI platforms are solutions for retrieving and analyzing business information for more effective decision-making (Bustamante et al., 2020). BI incorporates technologies such as Data Warehouse, online analytical processing, data exploration, benchmarking, text search, and prospective analysis (Williams, 2016). The strength of BI lies in its ability to manage various internal and external resources in the form of structured and unstructured data. Craft industries can leverage this platform to analyze market trends, evaluate product performance, and identify foreign market opportunities. Thus, businesses can identify which countries have great potential for exporting handicraft products and adjust their strategies to optimize business opportunities in these markets. As such, using BI helps identify potential barriers and issues in Indonesia's handicraft sector. By understanding these issues, the government and businesses can collaborate to address them and create a more conducive business environment for product exports.

Previous research has been conducted by Sufi et al. (2022) to analyze tropical cyclones in Australia using regression, clustering, and convolutional neural network methods. In their study, the researchers aimed to understand Australian tropical cyclones using artificial intelligence (AI) methods by analyzing data on tropical cyclone occurrence over four decades to reduce the adverse impacts of cyclones. The research developed a BI platform distributed on iOS, Android, and Windows for researchers or disaster strategists to use as a decision support system. The results showed that the analysis method could provide insights and knowledge in answering some of the research questions in the study. In another study, Bustamante et al. (2020) developed BITOUR as a BI platform for Tourism Analysis. This platform integrates collaborative data (Twitter, OpenStreetMap, Tripadvisor, and Airbnb) into a BI system that brings opportunities to support the decision-making process in improving tourism competitiveness. Through data integration, BITOUR makes it possible to analyze and visualize the data to answer several questions related to tourists' favorite places, average stay time, and visitors' views of several destinations.

The research objective in this study is the visualization of export development data of the craft industry using a BI platform to analyze its distribution, trends, and forecasting as an effort to accelerate the export of craft industry commodities in the province of West Java (Indonesia). The analysis methods used are clustering using k-means, time series analysis, and forecasting using exponential smoothing and compound annual growth rate (CAGR). The data used for the analysis process is data on the development of craft industry exports in the province of West Java from 2018 to 2022.

This study uses k-means clustering, time series analysis, exponential smoothing, and CAGR methods to analyze the handicraft industry's distribution, trends, and forecasting. Data analysis often involves grouping data based on specific attributes. Bivariate clustering, in particular, focuses on clustering data based on two variables (Atem et al., 2012; Halperin and Heath, 2020). This technique has many applications in various fields, including computer science, social science, economics, and biology. One of the most common approaches to bivariate clustering is k-means clustering, which seeks to group data based on similarity in a two-dimensional space (Morissette and Chartier, 2013). Another helpful method is hierarchical clustering, which builds a hierarchical structure of data groups based on the degree of similarity between variables (Sebastiani and Perls, 2016). Various studies have applied bivariate clustering to identify patterns of relationships between variables. For example, economics can be used to identify patterns of economic growth in different regions based on economic indicators (Zhou, 2021). In computer science, it can be used to cluster users based on their behavior in certain features (Prasad et al., 2020).

Time series analysis comprises sequential quantitative measurements (Kılıç and Uğur, 2018). There are two types of time series: the temporal series, which consists of nominal symbols in a specific alphabet, and the time series, which are continuous sequences with actual value elements (Aghabozorgi et al., 2015). The main characteristic of a time series is that its feature values change over time. Each point in the time series represents one or more observations recorded sequentially. Time series data can be found in various scientific disciplines, including science, engineering, business, finance, economics, biomedicine, and the government sector (Moraffah et al., 2021). Although the time series consists of many data points, they can often be considered single entities. However, as patterns in time series can vary from frequently occurring to infrequently occurring, various research challenges arise, such as developing methods for detecting dynamic changes in a time series, identifying anomalies, performing intrusion detection, controlling processes, and recognizing unique characteristics in this time series data (Shah et al., 2021). According to Maçaira et al. (2018), time series analysis involves analyzing dynamic systems of input and output series associated with a particular function. Despite the assorted possible purposes, the various techniques in this field all attempt to produce reliable and accurate output by estimating existing functions and inputs. Time series techniques can be grouped into two main categories: univariate and multivariate. In a univariate approach, outcomes are described by various components such as fixed shares, trends, and stable seasonal patterns, and in many cases, including lagged time series elements. Multivariate methods consider the impact of other variables on output behavior to enhance the representation of involved transfer functions (Bohm et al., 2013).

Exponential smoothing is a method to forecast trends and supply needs (Ferbar Tratar et al., 2016). This method is often used in the business world because it can provide reasonable estimates without requiring high statistical complexity. However, there are several aspects to consider when using it. A critical aspect of using exponential smoothing is the selection of suitable parameters (Hyndman and Athanasopoulos, 2013). Prediction validation is one method that helps determine these parameters. In prediction validation, the data is divided into training and test data. The training data is used to determine the appropriate smoothing parameters, often to minimize prediction error altogether. A validation sample is then used to test how well the method predicts data that is not yet visible using a metric such as the average absolute percentage error. In addition, some organizations use the trend-corrected exponential smoothing method or other methods appropriate to the nature of their data. This kind of research aims to measure the effectiveness of the traditional exponential smoothing method compared to an informed criterion-based approach in selecting forecasting methods. With a better understanding of the strengths and limitations of the exponential smoothing method, organizations can make better decisions in business planning, reduce purchasing costs, optimize inventory, and create a win-win situation with suppliers (Dong, 2022).

CAGR signifies the yearly growth rate observed throughout a specific duration encompassing multiple years (Van Genuchten and Hatton, 2012). CAGR mitigates the impact of periodic changes and removes the need for arithmetic methods (Sharma and Sharma, 2015). It is a valuable tool for comparing growth rates across various datasets, such as the consumption growth of a commodity. To compute CAGR, one must know the initial and final investment values and the duration of the investment period. This metric is extensively used among investors, analysts, and the business world for decision-making processes as it provides a consistent and easily interpretable measure of growth. Researchers and financial analysts have also extensively explored the application of CAGR in investment analysis, valuation, and forecasting, emphasizing its relevance in estimating future cash flows, valuation, and strategic planning (Rajeswari, 2020; Vijayalakshmi and Sathishkumar, 2018).

This research used a BI platform to analyze the distribution, trends, and forecasting of export commodities in the craft industry in West Java. With a deep understanding of the potential of craft products that can compete in the global market, business actors will be better prepared to face competition in the international market. Information technology solutions such as BI systems are invaluable tools for directing and providing strategic information. This research will provide a more accurate view and positively impact the development of the craft industry in West Java and its contribution to the regional and national economy.

## 2. Materials and methods

The main stages carried out in this study are divided into four, namely (1) data collection and data transformation stage, (2) data integration into the data warehouse stage, (3) data visualization stage, and (4) data analysis stage based on distribution, trends, and forecasting as shown in Fig. 1. The explanation of each process is described in sections 2.1, 2.2, 2.3, and 2.4.

### 2.1. BI data sources

This study used primary and secondary data to analyze the export data of the craft industry based on its distribution, trend, and forecasting. The scope of this study is data on the development of the craft industry exports in the province of West Java from 2018 to 2022. Preliminary data were obtained from the Central Statistics Agency (BPS) for West Java province published via the BPS website (https://bps.go.id/exim/) with the following data filters: (1) The selected HS Code are two digits related to craft export commodities: 42 for articles of leather; 44 for wood and articles of wood; 45 for cork and articles of cork; 46 for manufactures of plating materials; 61 for articles of apparel and clothing accessories (knitted); 68 for articles of stone, cement, asbestos, mica or similar materials; 69 for ceramic products; 70 for glass and glassware; 71 for precious metals and jewelry/precious stones; 82 for tools, implements of base metal; 83 for miscellaneous articles of base metal; and 97 for works of arts, collectors pieces and antiques; (2) The selected export years were from 2018 to 2022 for all destination countries; and (3) The selected shipping ports were the ports closest to the scope of West Java province: Soekarno-Hatta (IDCGK), Tanjung Priok (IDTPP), and Bandung – Husein Sastranegara (IDBDO).

The resulting data is presented as tabular pivot data in Excel, summarized based on net value (USD) and net weight (Kg). For analysis needs, the data source format was adjusted by transforming the pivot table into an unpivot table. This step was conducted during the data preparation stage. The net value (USD) table (Fig. 2) and net weight (Kg) table have the same table format where the export trade data is displayed as pivot data based on year, HS code, country, port, and month. An empty data cell indicates no transaction value in that condition. Fig. 2 shows the transformation process from pivot data to unpivot data. This process produced a data table of 9,846 rows for 2018 transaction data, 9,838 rows for 2019, 9,127 rows for 2020, 9,878 rows for 2021, and 9,990 rows for 2022, with 48,679 rows of data overall. This table is the primary source (fact table) in the export transaction analysis process, which was then integrated into the BI platform. The data attributes were HS code, country, port, month, year, net value (USD), and net weight (Kg), as shown in Fig. 2.

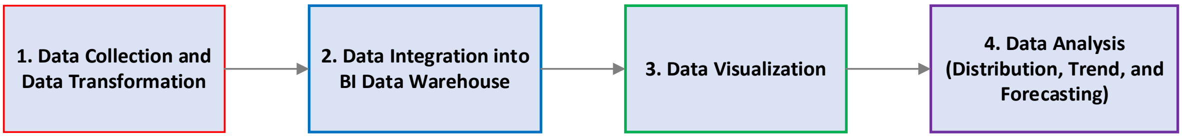
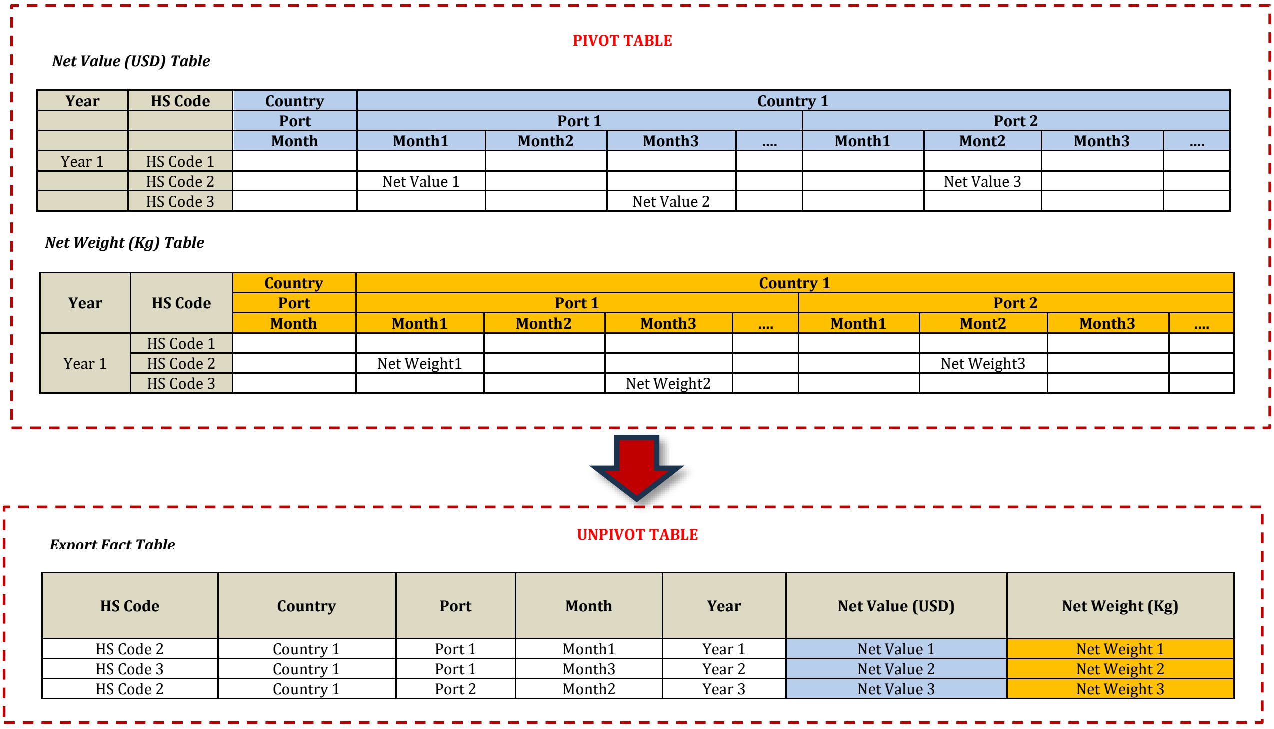



**Fig. 1:** Stages of BI implementation for craft industry export data analysis




| Year | HS Code | Country | Country 1 | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Port | Port 1 | | | | Port 2 | | | |
| | | Month | Month1 | Month2 | Month3 | .... | Month1 | Mont2 | Month3 | .... |
| Year 1 | HS Code 1 | | | | | | | | | |
| | HS Code 2 | | Net Value 1 | | | | | Net Value 3 | | |
| | HS Code 3 | | | | Net Value 2 | | | | | |



| Year | HS Code | Country | Country 1 | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Port | Port 1 | | | | Port 2 | | | |
| | | Month | Month1 | Month2 | Month3 | .... | Month1 | Mont2 | Month3 | .... |
| Year 1 | HS Code 1 | | | | | | | | | |
| | HS Code 2 | | Net Weight1 | | | | | Net Weight3 | | |
| | HS Code 3 | | | | Net Weight2 | | | | | |



| HS Code | Country | Port | Month | Year | Net Value (USD) | Net Weight (Kg) |
|---|---|---|---|---|---|---|
| HS Code 2 | Country 1 | Port 1 | Month1 | Year 1 | Net Value 1 | Net Weight 1 |
| HS Code 3 | Country 1 | Port 1 | Month3 | Year 2 | Net Value 2 | Net Weight 2 |
| HS Code 2 | Country 1 | Port 2 | Month2 | Year 3 | Net Value 3 | Net Weight 3 |

**Fig. 2:** The process of transforming source data (export trade) from pivot data to unpivot data

Apart from primary data, secondary data was also required in the form of country data obtained from the World website (databank.worldbank.org) and export commodity data in the form of two-digit HS codes received from West Java's opendata website (opendata.jabarprov.go.id). This secondary data will be combined with primary data and put into the BI platform as dimension tables (Fig. 3). The data rows owned by the country table are 208 rows of data, and 12 rows of data for the commodity table.

## 2.2. BI data warehouse

ETL (extract-transform-load) technology was used to integrate the data into a BI platform. This technology allows various data formats from multiple sources to be loaded into a data warehouse (DW). ETL is the most essential part of a BI project, as the quality of BI output will depend on the data integration process (Pan et al., 2018). The BI platform used in this study is MS Power BI, which has capabilities similar to MS Excel but is very powerful in processing data for manipulation, analysis, and visualization (Becker and Gould, 2019). This platform allows BI stages to be conducted comprehensively, from the data integration, data analysis, and data visualization processes to deployment on the BI server, which can also be accessed as a web or mobile view. MS Power BI is easy for users who are used to working in an MS Office environment, especially for users responsible for visualizing information from various sources. Primary and secondary data that have been integrated into the BI data warehouse will then be formed into a data model and its relationships, generally based on the same reference value. The BI data warehouse model developed is a star schema model that divides data tables based on fact tables and dimension tables, as shown in Fig. 3. This model is suitable for implementing BI, where business data will be measured on several dimensions (Munawar and Munawar, 2023). As "Star" implies, the relationship form consists of several dimension tables and one fact table as the center. The fact table contains foreign key (FK) attributes that become the primary key (PK) in the dimension table, and this is the connectivity between the fact table and the dimension table (Iqbal et al., 2020). In total, one fact table (export trade) and three dimension tables (commodity, country, and year) were built in this study. The country dimension table contains data in the form of country codes and country names, and an export commodity dimension table includes data in the form of HS codes and commodity descriptions. A year dimension table was also formed, which stores the accumulated net value (USD) and net weight (Kg) per year.

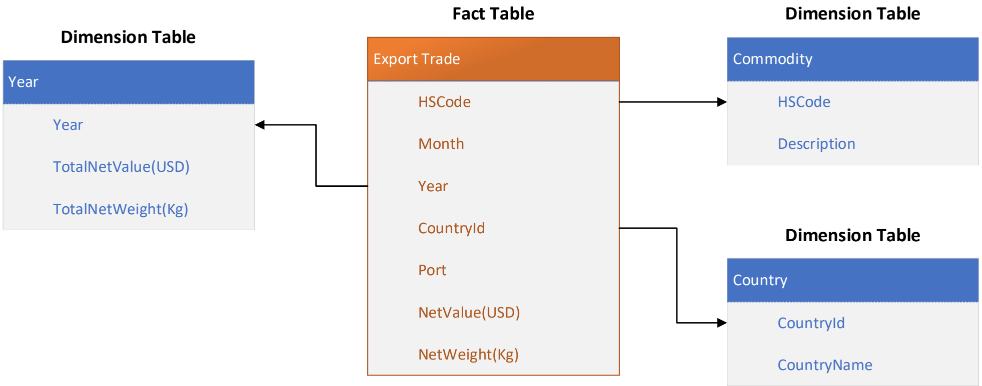



**Fig. 3:** Relational schema built with the star schema model

## 2.3. BI visualization

BI was employed to analyze export transaction data based on their distribution, trends, and forecasts. The aim was to determine the current export conditions based on historical data from 2018 to 2022 and export potential for the next four years (2023–2026) to provide insight and assist stakeholders in making decisions.

The methods used in the analysis process were (1) the k-means clustering method to understand the clustering of export destination countries based on the net value (USD) and net weight (Kg); (2) time series analysis to determine the export sales trend per craft export commodity annually, and (3) the exponential smoothing and the CAGR methods were used for forecasting analysis. Data visualization was designed according to the purpose of the data analysis. Thus, there were three visualization reports: (1) the export distribution analysis report, (2) the export trend analysis report, and (3) the export forecast analysis report. Table 1 shows the BI visualization mapping of the methods used, the visual components for displaying data, the information displayed, and related data sources.

## 2.4. BI analysis

### 2.4.1. Clustering

The export distribution analysis report was designed using five visual components associated with the Fact_ExportTrade and Dim_Country tables (Fig. 3) to display the distribution map of exports to destination countries, and the clustering was performed using the k-means clustering method, as shown in Table 1. MS Power BI provides this method through the "Automatically find cluster" analysis feature. A total of 3 clusters were formed in this study and grouped based on net value (USD) and net weight (Kg). The clustering process in k-means uses an Euclidian distance calculation consisting of 2 points, namely $p = (p_1, p_2)$ and $q = (q_1, q_2)$ to measure the distance to point $k$ or the so-called cluster centroid, and $x$ as the data point (Sufi et al., 2022). The calculation is by Eq. 1:

$$d(p, q) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2} \quad (1)$$

After each point is measured using the Euclidian distance, the closest distance to the cluster centroid (point $k$) is found using Eq. 2:

$$\underset{c_i \in C}{\operatorname{argmin}} dist(c_i, x)^2 \quad (2)$$

In this case, dist() shows the Euclidian distance result. Furthermore, the new centroid is calculated based on the average of each point in the cluster group. The calculation uses Eq. 3:

$$c_i = \frac{1}{|S_i|} \sum_{X_i \in S_i} X_i \quad (3)$$

Here, the set of all points allocated to the i-th cluster is denoted by $S_i$. Eq. 1 is used to calculate the Euclidian distance. Eq. 2 is used to assign points to cluster centers. Eq. 3 is used to obtain a new centroid by taking the average. This method is repeated several times until the centroid remains the same. After these iterations, $k$ number of cluster centroids are found, and the corresponding clusters are allocated to the data points.

**Table 1:** BI visualization mapping of methods, visual components, information, and data sources

| Visualization report | Method | The visual component used | Information displayed | Data source |
|---|---|---|---|---|
| a | b | Slicer | List of craft export commodities as a search filter | Dim_Commodity |
| | | Map | Map of export distribution to destination countries clustered based on net value (USD) | Dim_Country, Fact_ExportTrade |
| | | Scatter chart | Clustering of export destination countries for craft products based on net value (USD) and net weight (Kg) | Dim_Country, Fact_ExportTrade |
| | | Table | List of export destination countries along with information on net value (USD), net weight (Kg), and clusters | Dim_Country, Fact_ExportTrade |
| | | Donut chart – 1 | Percentage of net value (USD) based on country cluster | Dim_Country, Fact_ExportTrade |
| | | Donut chart – 2 | Net weight percentage (Kg) based on country cluster | Dim_Country, Fact_ExportTrade |
| c | d | Line chart | Annual export trends based on net value (USD) and net weight (Kg) for each craft export commodity | Dim_Commodity, Fact_ExportTrade |
| | | Table | List of craft export commodities along with information on net value (USD), net weight (Kg), up or down trend icon | Dim_Commodity, Fact_ExportTrade |
| | | Stacked area chart | Comparison of export trends based on net value (USD) for each craft export commodity each year | Dim_Commodity, Fact_ExportTrade |
| e | f | Table | List of export destination countries along with information on net value (USD), net weight (Kg), and clusters | Dim_Country, Fact_ExportTrade |
| | | Table | List of craft export commodities along with information on net value (USD), net weight (Kg), and upward or downward trend icons | Dim_Commodity, Fact_ExportTrade |
| | | Line chart – 1 | Forecasting graph based on net value (USD) using the exponential smoothing method | Fact_ExportTrade |
| | | Line chart – 2 | Forecasting graph based on net weight (Kg) using the exponential smoothing method | Fact_ExportTrade |
| | | Line chart – 3 | Forecasting charts based on net value (USD) using the CAGR method | Dim_Year |
| | | Line chart – 4 | Forecasting charts based on net weight (Kg) using the CAGR method | Dim_Year |

a: Export distribution analysis report; b: K-means clustering; c: Export trend analysis report; d: Time series analysis; e: Export forecasting analysis report; f: Exponential smoothing and CAGR

### 2.4.2. Time series analysis

The export trend analysis report used three visual components related to the Fact_ExportTrade and Dim_Commodity tables (Fig. 3). The time series components used are line charts and stacked area charts to display export trends per commodity per year. Trend measurement was performed simply by comparing the baseline net value (USD) in 2018 with the net value (USD) achievements in 2022. If the 2022 achievements > the 2018 baseline, then the trend is assumed to increase, and vice versa; if the 2022 achievements < the 2018 baseline, the trend is assumed to decrease.

### 2.4.3. Forecasting

The export forecasting analysis report was designed using six visual components in the form of tables and line charts. This report aims to show export forecasting for 2023 to 2026 using the exponential smoothing method and the CAGR method. MS Power BI, by default, uses the exponential smoothing method in forecasting. Therefore, this method was already available for the feature analysis on the line chart component. Exponential smoothing is a prediction method that calculates future values using the weighted values of the previous sequence of observations. As more previous observations are added, the weights will decrease regularly, giving the highest weight to the most recent observation. Exponential smoothing suggests smoothing the initial sequence and using the smoothed sequence to forecast the variable's future value of interest (Shastri et al., 2018). The stages performed in processing exponential smoothing are by Eq. 4 (Nirmala et al., 2021):

$$Ft + 1 = aXt + (1 - a)Ft - 1 \tag{4}$$

In this case, Ft+1 is the forecast for the period to t + 1, Xt is the period rill value to t (present), a is the smoothing constant (0 < a < 1), and Ft-1 is the forecast for the period to t-1 (previous). Trial and error are necessary for measuring the constant (alpha), where the values are compared using the interval between 0 < a < 1 (0.1 to 0.9).

The CAGR method implemented in this study was calculated using data analysis expression (DAX). DAX is a language used to develop data models in Power BI through four types: calculated tables, columns, measures, and security roles (Jolly, 2023). The steps taken for forecasting with CAGR with DAX in MS Power BI for 2023 - 2026 are as follows:

1. Calculate CAGR using the following formula:

$$POWER\ ((End\_Value - Start\_Value), DIVIDE(1, Periods)) - 1$$

2. Calculate forecast using the following formula:

$$Value\_2023 \rightarrow POWER\ (Value\_2022 * (1 + CAGR), 1)$$
$$Value\_2024 \rightarrow POWER\ (Value\_2022 * (1 + CAGR), 2)$$
$$Value\_2025 \rightarrow POWER\ (Value\_2022 * (1 + CAGR), 3)$$
$$Value\_2026 \rightarrow POWER\ (Value\_2022 * (1 + CAGR), 4)$$

## 3. Results and discussion

### 3.1. Export distribution analysis

This analysis was conducted to determine the distribution of craft commodities exported to destination countries. The clustering of destination countries was divided into 3 clusters using the k-means clustering method in MS Power BI with net value (USD) and net weight (Kg) as variables. Cluster 1 has 200 countries, such as Switzerland, Hong Kong, Australia, Germany, Netherlands, and more. Cluster 2 comprises six countries: Japan, the Republic of Korea, China, India, Malaysia, and the Philippines. Cluster 3 contains two countries: The United States and Singapore. The total net value (USD) for cluster 1 is 17.09 bn (36.39% of the 3 clusters combined), with the primary export commodities being HS codes 71 (9.3bn), 61 (4.0bn), 44 (1.4bn), 42 (0.9bn), and 70 (0.5bn). The total net value (USD) for cluster 2 is 6.68 bn (14.22% of the 3 clusters combined), with the primary export commodities being HS codes 61 (2.6bn), 44 (1.8 bn), 70 (0.6bn), 69 (0.5bn), and 42 (0.3bn). The total net value (USD) for cluster 3 is 23.20bn (49.39% of the 3 clusters combined), with the primary export commodities being HS codes 71 (10bn), 61 (10bn), 42 (2bn), and 44 (1bn). Based on the total net value (USD) obtained from 2018 to 2022, cluster 3 is the group of countries with the highest export value. However, it is different if we look at the total net weight (Kg), where cluster 2 is the group of countries with the highest export value, namely 4.11bn (46.73% of the 3 clusters combined). Fig. 4 shows the analysis report on the distribution of craft commodity exports and their cluster mapping.

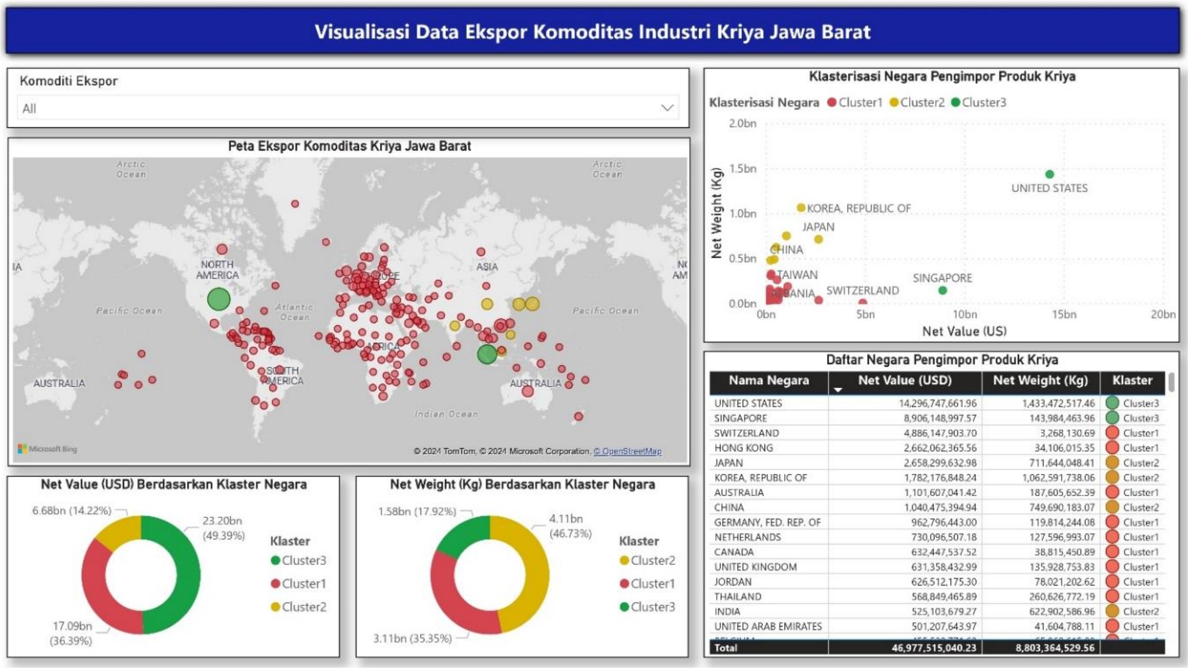



**Fig. 4:** Analysis report on the distribution of craft commodity exports

Table 2 shows the mapping of export commodities to the percentage of net value (USD) and net weight (Kg) of destination country clusters where the cells marked show the highest percentage values. These results indicate that the HS code 42 has the highest percentage in cluster 3; HS code 44 in cluster 2; HS code 45 in cluster 3; HS code 46 in cluster 1; HS code 61 in cluster 3; HS code 68 in cluster 2; HS code 69 in cluster 2 for the highest net value (USD) and cluster 1 for the highest net weight (Kg); HS code 70 on cluster 2; HS code 71 on cluster 3; HS code 82 on cluster 3; HS code 83 in cluster 2 for the highest net value (USD) and cluster 1 for the highest net weight (Kg); and HS code 97 in cluster 3 for the highest net value (USD) and cluster 2 for the highest net weight (Kg).

**Table 2:** Percentage of net value (USD) and net weight (Kg) for each cluster of export commodities

| HS code (2 digit) | Percentage by net value (USD) | | | Percentage by net weight (Kg) | | |
|---|---|---|---|---|---|---|
| | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 1 | Cluster 2 | Cluster 3 |
| 42 | 31.4% | 12.26% | 56.33% | 36.74% | 12.55% | 50.71% |
| 44 | 32.52% | 42.94% | 24.53% | 28.12% | 53.79% | 18.09% |
| 45 | 17.69% | 2.87% | 79.43% | 6.3% | 8.76% | 84.94% |
| 46 | 65.56% | 11.48% | 22.97% | 73.11% | 15.08% | 11.81% |
| 61 | 24.28% | 15.8% | 59.92% | 29.57% | 16.11% | 54.32% |
| 68 | 42.01% | 49.64% | 8.35% | 38.47% | 50.22% | 11.32% |
| 69 | 35.09% | 42.84% | 22.07% | 48.92% | 41.19% | 9.89% |
| 70 | 44.94% | 50.82% | 4.25% | 44.28% | 52.59% | 3.13% |
| 71 | 47.16% | 1.49% | 51.35% | 19.01% | 27.21% | 53.78% |
| 82 | 25.17% | 35.65% | 39.18% | 27.01% | 19.41% | 53.58% |
| 83 | 45.46% | 46.25% | 8.29% | 49.42% | 40.87% | 9.71% |
| 97 | 20.49% | 30.89% | 48.62% | 21.63% | 44.02% | 34.35% |

### 3.2. Export trend analysis

The export trend analysis was visualized in a line chart. This analysis measured each export commodity's annual net value (USD) and net weight (Kg) achievements. As seen in Fig. 5, export commodities with HS code 71 and HS code 61 show a high net value (USD) compared to other export commodities. Meanwhile, in terms of net weight (Kg), the highest export commodities are HS code 44 and HS code 70. The upward or downward trend for each commodity can be seen by comparing the export value at the baseline in 2018 with the export value in the last year in 2022. Several commodities that show an upward trend are HS codes 71, 61, 42, 70, 82, 68, 46, and 97. Conversely, commodities with a decreasing trend are HS codes 44, 69, 83, and 45. The visualization in Fig. 4 shows a decreasing trend in exports in 2020; commodities with HS codes 61, 44, 69, 83, 68, and 45 experienced the most significant decline, and commodities with HS codes 42, 70, and 82 experienced stagnant growths. In contrast, other commodities with HS codes 71, 46, and 97 experienced significant increases. This condition is likely influenced by the global economic situation during the COVID-19 pandemic, where almost every country's gross domestic product (GDP) was impacted. The visualization of export trends can be seen in more detail by selecting the HS code to be filtered, as shown in Fig. 6. When HS code 61 is selected, the graphic display will adjust to the export achievements of that commodity.

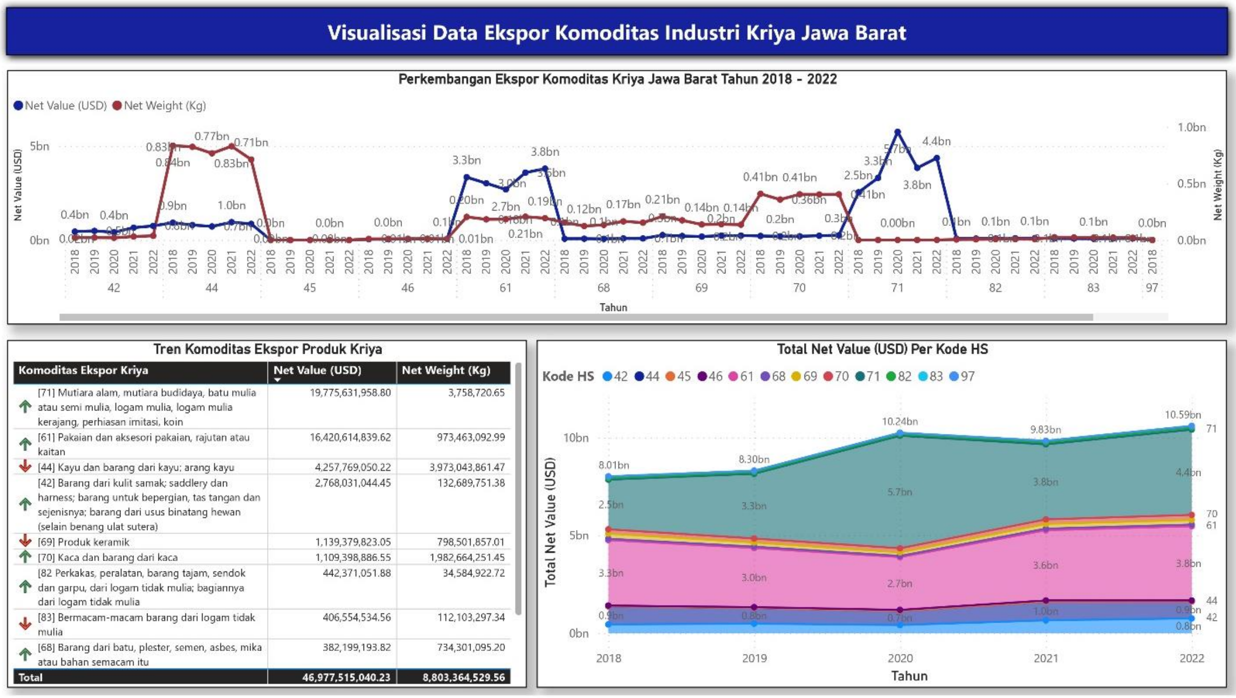



**Fig. 5:** Craft commodity export trend analysis report

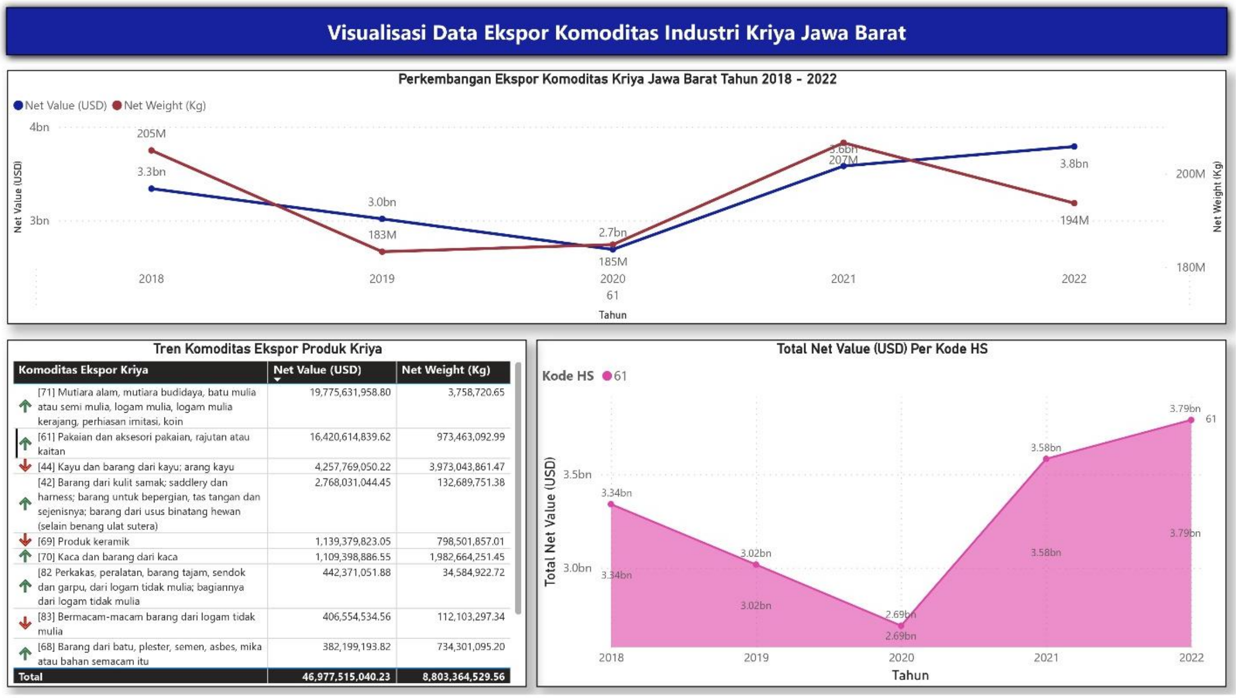



**Fig. 6:** Example of visualization to see export trends in HS code 61

### 3.3. Export forecasting analysis

This study used two methods for its forecasting analysis, namely the exponential smoothing method, which has been provided for clustering features in MS Power BI, and the compounded annual growth rate (CAGR) method, which is implemented using DAX (example of calculation in Table 3).

The forecasting of the export value for 2023 to 2026 based on net value (USD) exhibits an increasing trend in both methods. However, the forecasting export value based on net weight (Kg) has a stagnant trend in exponential smoothing and a decrease in CAGR, as shown in Fig. 7. A more in-depth analysis of each export commodity's forecasts for 2023 to 2026 is as follows: (1) HS code 42 will experience an increasing trend in both net value and net weight; (2) HS code 44 will experience a stagnant trend in both net value and net weight; (3) HS code 45 will experience a decreasing trend for net value and net weight; (4) HS code 46 will experience an increasing trend for net value and stagnation for net weight; (5) HS code 61 will experience a stagnant trend for both net value and net weight; (6) HS code 68 will experience a stagnant trend for both net value and net weight; (7) HS code 69 will experience a decreasing trend for net value and net weight; (8) HS code 70 will experience a stagnant trend in net value and a fluctuating increase in net weight; (9) HS code 71 will experience a stagnant trend for net value and an increasing trend for net weight; (10) HS code 82 will experience an upward trend for both net value and net weight; (11) HS code 83 will experience a stagnant trend in net value and a decline in net weight; and (12) HS code 97 will experience an upward trend in net value and stagnation in net weight. The following are forecasting results for 2023 to 2026 based on the primary export destination countries: (1) United States will experience an increasing trend for both net value and net weight; (2) Singapore will experience a stagnant trend for both net value and net weight; (3) Switzerland will experience an increasing trend in net value and stagnation in net weight; (4) Hong Kong will experience a stagnant trend in net value and a decline in net weight; (5) Japan will experience a stagnant trend in net value and an increase in net weight.

### 3.4. Discussion

Some of the findings resulting from this research are as follows:

**Table 3:** DAX implementation for forecasting used the CAGR method

| Calculate CAGR | Calculate forecast |
|---|---|
| CAGR =<br>VAR LastYear = [LastYear]<br>VAR FirstYear = [FirstYear]<br>VAR No_Of_Year= [LastYear] - [FirstYear]<br>RETURN<br><br>POWER (<br>DIVIDE (<br>CALCULATE (SUM ('Dim Year'[TotalNetValue]),'Dim Year'[Year]=LastYear),<br>CALCULATE (SUM ('Dim Year'[TotalNetValue]),'Dim Year'[Year]=FirstYear)<br>),1 / No_Of_Year) - 1 | Forecast =<br>VAR LastYear = [LastYear]<br>VAR No_Of_Year = SELECTEDVALUE ('Dim Year'[Year]) - [LastYear]<br>RETURN<br><br>IF (<br>SELECTEDVALUE ('Dim Year'[Year]) >= LastYear,<br>CALCULATE (SUM ('Dim Year'[NetValue]), 'Dim Year'[Year] = LastYear)<br>* POWER ((1 + [CAGR]), No_Of_Year)<br>) |

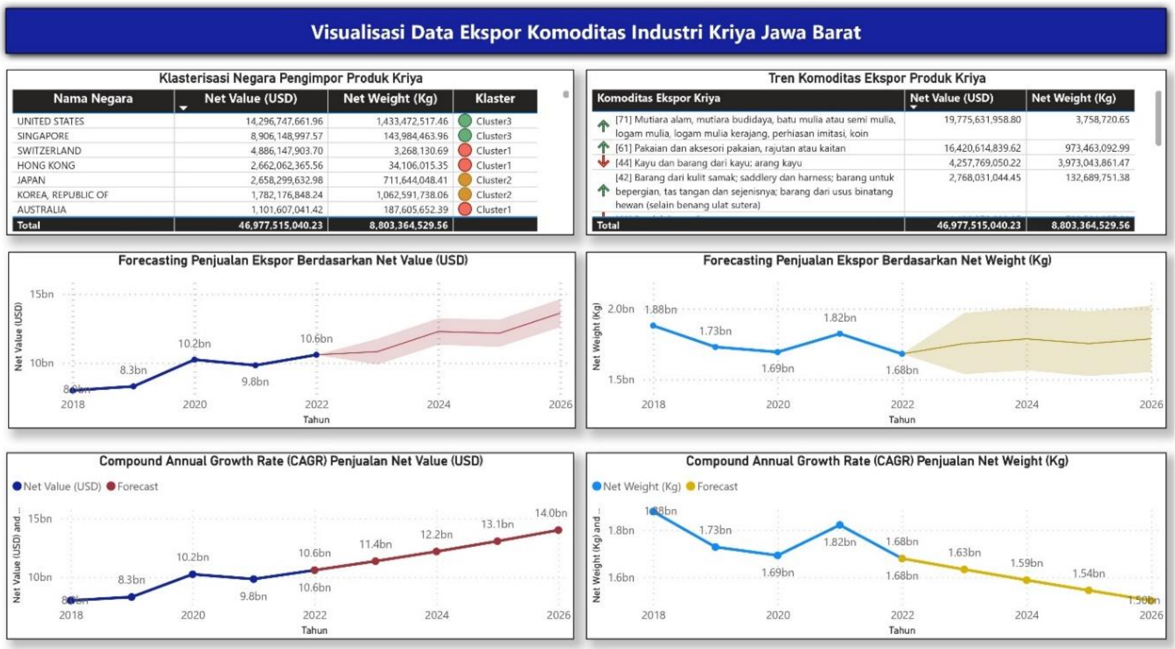



**Fig. 7:** Analysis report on craft commodity export forecasting for 2023 to 2026

- Distribution analysis: Cluster 3 is a list of the most dominant countries as export destinations for the West Java craft industry, where based on net value (USD), imports several main commodities such as HS Code 42, HS Code 45, HS Code 61, HS Code 71, HS Code 82, and HS Code 97. Likewise, with export value based on net weight (Kg), commodities with HS Code 42, HS Code 45, HS Code 61, HS Code 71, and HS Code 82 are the main commodities most imported by Cluster 3. However, cluster 3 only consists of two countries, namely the United States and Singapore. In Singapore, HS Code 71 has an import percentage of 97.6% compared to other commodities with a net value (USD) of 8.63bn. Meanwhile, in the United States, the most imported commodity is HS Code 61 (69.48%), with a net value (USD) of 9.74 billion. Cluster 2 is the next list of export destination countries after Cluster 3, where based on net value (USD), the main commodities most widely exported are HS Code 44, HS Code 68, HS Code 69, HS Code 70, and HS Code 83. Meanwhile, based on net weight (Kg), Cluster 2 is the main export destination for HS Code 44, HS Code 68, HS Code 70, and HS Code 97 commodities. Compared to other clusters, Cluster 1 has the lowest export value but is the main destination for HS Code 46 commodities. Judging from the distribution percentage, several other potential commodities in Cluster 1 are HS Code 68, HS Code 69, HS Code 70, HS Code 71, and HS Code 83. Therefore, many things still need to be explored to improve other commodities in Cluster 1.
- Trend analysis: There are eight export commodities with an increasing trend, namely HS Code 71, HS Code 61, HS Code 42, HS Code 70, HS Code 82, HS Code 68, HS Code 46, and HS Code 97. HS Code 71 is a significant commodity with a strong increasing trend, namely 74.07% in 2020 compared to the previous year. This happened due to an increase in the value of exports to Switzerland (CH) by 1.9bn, the United States (US) by 0.5bn, Australia (AU) by 0.2bn, and Hong Kong (HK) by 0.1bn, as shown in Fig. 8. Export commodities with a decreasing trend are HS Code 44, HS Code 69, HS Code 83, and HS Code 45. However, the commodity with the most significant decreasing trend is HS Code 45, which in 2021 experienced a decline of -99.46%. This was due to a decrease in the value of exports to Singapore (SG) by -46K, Saudi Arabia (SA) by -14K, United Arab Emirates (AE) by -7K, and Kuwait (KW) by -1K as shown in Fig. 9.

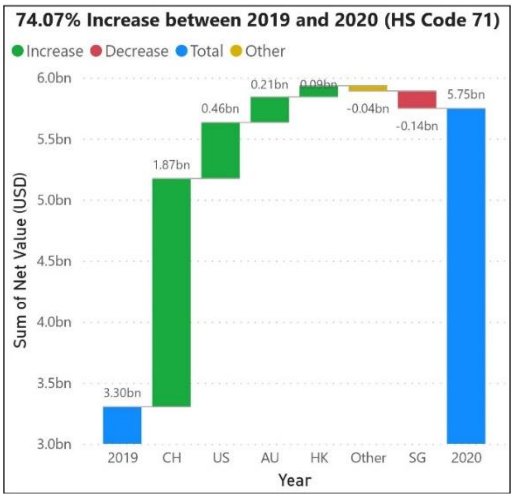



**Fig. 8:** Analysis of the increase in export value of 74.07% in HS code 71

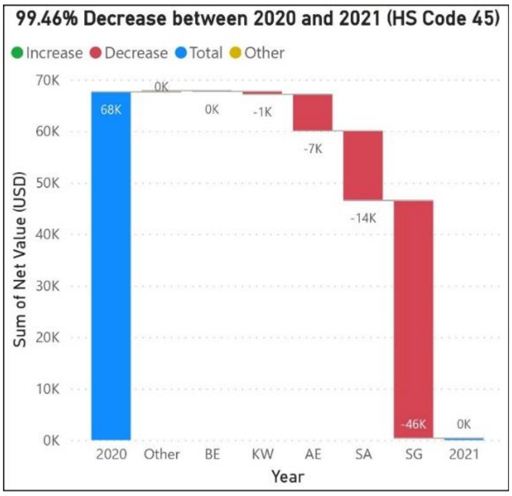



**Fig. 9:** Analysis of the decrease in export value of -99.46% in HS code 45

- Forecasting Analysis: Based on the forecasting analysis that has been carried out for 2023 – 2026, the average results of the exponential smoothing and CAGR methods show an increase in net value (USD) from 10.6bn in 2022 to 13.8bn in 2026 for the net weight (Kg) tends to stagnate or decrease from 1.68bn in 2022 to 1.64bn in 2026. This shows that demand for craft industry export commodity products in the future will be smaller or lighter in weight, but the price will increase. Several commodities with the largest net weight (Kg), such as HS Code 44, HS Code 70, HS Code 61, HS Code 69, and HS Code 68, need to pay attention to these conditions.
- BI implementation strategy based on study results: This research has implemented BI in analyzing craft industry export data based on distribution, trends, and forecasting using various analytical methods such as k-means clustering, time series analysis, exponential smoothing, and CAGR. The method used can help the data analysis process understand the current export market situation so that it can be used by business people and the government to make effective decisions. The stages carried out in this study are in accordance with the scope analysis needs. For future development, research can also be developed in a broader scope, namely not only in West Java province but also in other provinces or even nationally. Several things that need to be considered are the availability of valid data sources, a clean data integration process, appropriate analysis methods, and a platform that suits the needs. This research only produces a BI prototype in the form of a dashboard display. In the

future, a strategy is also needed to distribute it on other platforms such as Android, iOS, Web, and Windows Desktop to expand its use.

## 4. Conclusion

This study analyzes the distribution of Indonesia's craft commodity exports, trends, and forecasts. The export distribution analysis grouped destination countries into three clusters based on net value (USD) and net weight (Kg). Based on the clustering results, the total net value (USD) dominance of Cluster 3 consists of the United States and Singapore. Cluster 2, which comprises six countries, leads in terms of net weight (Kg). The mapping of export commodities into these clusters also shows different patterns across HS codes, with Cluster 3, consisting of 200 countries, showing the highest percentages for some key codes. Analysis of export trends, visualized through line charts, shows the leading performance of HS codes 71 and 61 in terms of net value (USD), while codes 44 and 70 excel in terms of net weight (Kg). The trends vary, with some commodities experiencing growth and others declining, mainly affected by the global economic situation during the COVID-19 pandemic. The forecast analysis used exponential smoothing and CAGR methods, which showed an upward trajectory in net value (USD) forecasts but stagnation or decline in net weight (Kg) forecasts. Detailed forecasting for specific export commodities and destination countries provides valuable guidance for future export strategies. This research provides important insights for industrial development and global competitiveness, offering a foundation for crafting effective and sustainable export policies in the future.

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## Compliance with ethical standards

### Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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