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NEXUS BETWEEN THRIFTING AND GDP GROWTH IN INDONESIA'S TEXTILE AND WEARING APPAREL MANUFACTURING: ARDL AND SENTIMENT ANALYSIS APPROACH

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ABSTRACT

Introduction: The rise of used clothing imports has sparked concerns about its economic impact, particularly on Indonesia's textile and apparel industry.
Methods: This study employs a mixed-methods approach, combining quantitative (ARDL model) and qualitative (sentiment analysis) methods. It analyzes GDP, Google Trend Index (GTI), and used clothing import data from 2018–2023 to assess the economic impact of thrifting.
Results: This study analyzes the impact of thrifting on the GDP of Indonesia's textile and apparel industry subsector. The findings indicate that thrifting has a significant negative effect on the sector's GDP, while sentiment analysis reveals that 81.90 percent of public sentiment on Twitter expresses positive views toward thrifting.
Conclusion and suggestion: This study concludes that thrifting harms the GDP of Indonesia's textile and apparel industry subsector. This finding is reinforced by the high public interest in thrifting, as reflected in the predominantly positive sentiment on Twitter. In response, policymakers and industry stakeholders should strengthen the enforcement of existing regulations and focus on enhancing the competitiveness of local products.

INTRODUCTION

In recent years, the culture of buying used clothes has been growing (Oscario, 2023). In Indonesia, the thrifting phenomenon has exploded everywhere, even though the buying and selling of used clothes has long existed and has its own local names in different regions (Aswadana et al., 2022). Thrifting allows consumers to get items at a lower price than their original brand price (Saputro et al., 2024). Beyond being a cos-saving practice, thrifting provides a recreational experience. Consumers engage in the process of searching for unique or high-quality used clothing, which adds an element of enjoyment to the activity (Bardhi & Arnould, 2005).

Imports of used clothing are considered as one of the factors that can accelerate the decline of the textile and clothing industry. According to Brooks (2013), the large-scale import of used clothing can disrupt the local textile and garment industry, as local products struggle to compete with the low prices of imported used goods. This has the potential to reduce the revenue of domestic manufacturers and decrease the contribution of the textile and apparel industry to GDP. Kandiero (2005) points out that the liberalization of the used clothing market had a significant impact on the textile and clothing industry in Malawi. It is noted that clothing produced in Malawi tends to be more expensive than imported used clothing, making it difficult for many large factories to compete with the lower prices of the used clothing industry, ultimately forcing them to close.

In Africa, the trade in used clothing is not merely a chain of economic transactions extending from developed to developing countries but also part of a clothing commodity provision system that relies on and is interconnected with the region’s economic liberalization, existing international trade geography, and cultural transformations in dress (Fine, 2002; Hansen, 2002). Similarly, in Indonesia, the rise of thrifted goods sales negatively impacts local businesses, particularly MSMEs, as imported second-hand products are often sold at lower prices than domestically produced goods that comply with standards and tax regulations. This weakens the competitiveness of local industries, potentially leading to business closures, rising unemployment, and slower economic growth (Saputro et al., 2024).

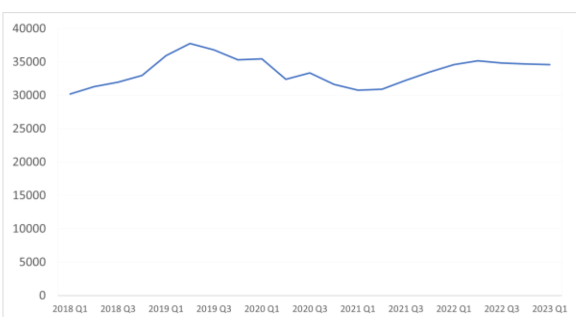

Figure 1. 2010 Constant Price GDP Graph of the Textile and Apparel Industry Sub-Sector (Billion Rupiah), 2018 - 2023

Source: BPS-Statistics Indonesia

Figure 2. 2010 Constant Price GDP Graph of the Textile and Apparel Industry Sub-Sector (kg), 2018 - 2023

Source: BPS-Statistics Indonesia

Figure 1 illustrates the fluctuations in the constant 2010 price GDP of the textile and apparel industry subsector from 2018 to 2023. Overall, the GDP experienced an upward trend, peaking at 37,769.8 billion IDR in the second quarter of 2019, before starting to decline after the fourth quarter of 2019, reaching 34,580.8 billion IDR in the first quarter of 2023. Meanwhile, Figure 2 shows significant fluctuations in used clothing imports, with a sharp surge in the fourth quarter of 2019, reaching 308,831 kg, far exceeding the previous quarters. This pattern suggests that the rise in used clothing imports may have contributed to the weakening of the domestic textile industry, as increased competition from cheaper imported goods challenges locally produced products. However, the recorded import figures may not accurately reflect the actual conditions, as numerous cases of illegal imports are not captured in official data. Yaneski (2018) found that the widespread smuggling of imported goods, particularly used clothing, is facilitated by weak and inconsistent regulations. This aligns with Birahayu (2020), who stated that the illegal importation of used clothing harms national finances, as these goods enter the country without import duties. Given the high prevalence of smuggling, official data likely underestimates the true volume of used clothing imports, suggesting that their impact on the local textile industry may be greater than what is reflected in official statistics.

Although thrifting has become a significant global phenomenon, research on its economic impact, particularly in Indonesia, remains limited. Existing studies tend to focus on its environmental effects and consumer behavior, while in-depth analyses of its influence on economic growth, the local textile industry, and trade policies are still lacking. Moreover, studies that integrate statistical approaches, such as macroeconomic data modeling, with qualitative methods, such as sentiment analysis to understand public perceptions of thrifting, are scarce. This research aims to address these gaps by providing a comprehensive analysis of thrifting's economic impact through a combination of econometric modeling and big data-driven sentiment analysis.

Therefore, to address the existing research gap, further analysis is needed to examine the impact of thrifting on the GDP of the textile and apparel industry subsector. This study employs the ARDL approach for modeling and Sentiment Analysis to understand public sentiment toward this phenomenon. The data utilized include GDP data from BPS, the Google Trends Index (GTI) as an indicator of search trends related to thrifting, and Twitter data scraping to analyze public sentiment on this activity. This approach is expected to provide a more comprehensive understanding of its impact on the local industry.

LITERATURE REVIEW

GDP of Textile and Wearing Apparel Industry Subsector

Gross Domestic Product (GDP) is defined as the market value of all final goods and services produced within a country in a given period of time. This definition indicates that GDP measures total expenditure in the economy while also reflecting the total income generated from the production of goods and services (Mankiw, 2015). GDP is an indicator that describes the country's economy; an increase in GDP reflects an increase in remuneration for factors of production used during production (Jane et al., 2024; Kamal et al., 2024; Pramesthy et al., 2024; Yuliana et al., 2024). More than that, GDP also makes it possible to measure the extent of government policy in terms of a country's economy.

In the compilation of GDP by industry, the classification used encompasses seventeen industry categories, including the manufacturing industry (BPS-Statistics, 2024). In the manufacturing industry category, there are sixteen sub-industries, one of which is the manufacture of textiles and wearing apparel. The textile industry encompasses the entire process of textile fiber processing, from preparation and spinning to weaving, textile finishing, and the production of non-clothing textile goods such as bed sheets, tablecloths, curtains, blankets, and carpets. Meanwhile, the apparel industry focuses on the manufacturing of various types of clothing, both ready-to-wear and custom-made, using a wide range of materials, including woven fabrics, knitted fabrics, and leather. This industry includes the production of garments for all age groups, both traditional and modern, as well as the manufacture of accessories and fur-based clothing (BPS-Statistics, 2020). Thus, the GDP of the manufacture of textiles and wearing apparel subsector represents the added value of goods and services generated by all businesses in this subsector in Indonesia over a specific period.

Thrifting

The term "thrift" is often associated with second-hand or pre-owned goods, the majority of which originate from overseas. These items are not limited to used clothing but also include bags, shoes, and various accessories from various brands (Yoliandri, 2023). Thrifting refers to the practice of purchasing second-hand goods, which has become an established consumption culture in the contemporary era. This activity has long been widespread and is increasingly favored by various social groups, particularly young people. The growing prevalence of thrifting has contributed to the expansion of the used clothing trade, with numerous thrift stores importing used garments (Syam & Ichwan, 2023).

Google Trends Index (GTI)

Google trends data are increasingly utilized in the social sciences and related fields due to their ability to reflect search interest over time (Trends Help, 2025). The platform provides relative search volumes (RSVs) for specified time frames—monthly, weekly, daily, or hourly—ranging from 0 to 100. This scale, also referred to as the google trends index (GTI), represents the relative popularity of a search term. A value of 100 indicates the peak search interest within the selected period, while other values are expressed as a proportion of this maximum. For instance, an RSV of 50 indicates that the search term was queried at 50 percent of the highest recorded search volume during the observed time frame (Gummer & Oehrlein, 2024).

RESEARCH METHODS

Data

The data used in this study consists of secondary data from BPS-Statistics Indonesia and big data sources, including the Google Trends Index (GTI) and Twitter scraping data, as summarized in Table 1. Thrifting is represented in this study by two variables: used clothing import data and GTI. The used clothing import data was obtained from the BPS-Statistics Indonesia website (bps.go.id) using HS code 63090000 (worn clothing and other worn articles), covering the period January 2018 to March 2023.

Additionally, Gross Domestic Product (GDP) data for the textile and apparel industry subsector, measured at current prices, is included. The GDP dataset spans from the first quarter of 2018 to the first quarter of 2023. Besides data from BPS-Statistics Indonesia, this study also incorporates big data from Google Trends. The GTI dataset covers the period January 2018 to March 2023 and is based on the search query "thrift clothes" retrieved from Google Trends.

Table 1. Research data period

Data	Period	Frequency	Analysis
GTI	2018 – 2023	Monthly	ARDL
Used clothing import	2018 – 2023	Monthly	ARDL
GDP of textile and apparel industry subsector	2018 – 2023	Quarterly	ARDL
Scrapping twitter	2023	Daily	Sentiment

Source: Primary data (2023)

ARDL (Autoregressive Distributed Lag)

The ARDL model is a development of the Error Correction Model (ECM) model, which can explain long-term (long-run) and short-term (short-run) relationships. The ARDL model has simple steps and can be applied to several samples. ARDL can simultaneously estimate long and short-term components and overcome the problems of autocorrelation and omitted variables. Not only that, the estimator in the long term is consistent so that it can provide valid results (Widodo et al., 2013).

The first step is the stationarity test, conducted using the Augmented Dickey-Fuller (ADF) test to detect the presence of unit roots. If the series is non-stationary, differencing is applied. The optimal model is selected based on the Akaike Information Criterion (AIC). The cointegration test follows, using the bounds test to examine the long-term relationship between variables. If cointegration is confirmed, short-term estimation is performed using the Error Correction Model (ECM) to analyze variable adjustments in response to short-term fluctuations. This is followed by long-term estimation to assess the sustained relationship between variables within the ARDL framework.

The next stages involve classical assumption and stability tests to ensure estimation reliability. Homoscedasticity is tested using the Breusch-Pagan-Godfrey (BPG) test, where a p-value above 5% confirms constant error variance. Autocorrelation is assessed using the Run Test, which checks for correlations between residuals. If residuals are uncorrelated, they are considered random, fulfilling the non-autocorrelation assumption (Ghozali, 2016).

Sentiment Analysis

Conducting sentiment analysis involves several stages, beginning with scraping, which is the process of collecting public opinion data from websites or social media. In this study, Twitter is used as the data source, and data collection is performed using the Python library "tweepy" (Salim et al., 2021) . Tweepy allows Python to access Twitter data through its API (Utami et al., 2021). The query used for data collection is "thrift", filtered for Indonesian-language tweets.

Following data collection, tweets are annotated through both human judgment and machine learning. Sentiment classification consists of three categories: negative (0), indicating rejection of thrifting; positive (2), reflecting support for thrifting; and neutral (1), representing an impartial stance. Human-labeled data serves as a reference to ensure annotation quality, which is then utilized for training the machine learning model to label the remaining data. After labeling, the collected tweets undergo preprocessing to enhance data quality and consistency in analysis. Text preprocessing transforms unstructured text into a structured format by eliminating noise (Afifah et al., 2021). The process begins with a missing value check, as incomplete data can reduce classification accuracy. Case folding standardizes text by converting all letters to lowercase (Resyanto et al., 2019), ensuring uniform word recognition. The cleaning stage removes punctuation, numbers, RTs, mentions, and URLs to minimize classification errors (Prakash & Aloysius, 2019). Stopwords—common words without significant meaning—are

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eliminated using the NLTK library, with filtering adapted for the Indonesian language (Pradha et al., 2019). Lastly, lemmatization converts words to their base form, improving text normalization. Compared to stemming, lemmatization is more precise as it considers vocabulary and word morphology, making it preferable for text analysis (Balakrishnan & Lloyd-Yemoh, 2014). To prepare the data for machine learning, feature extraction is performed using TF-IDF, which converts text into numerical representation. TF measures word frequency within a document, while IDF assigns weight based on word rarity across documents, ensuring better text differentiation.

This study employs supervised machine learning for sentiment classification, using expert-labeled data to train the model and predict unlabeled data, making it ideal for classification (Miller et al., 2020). LightGBM, a gradient boosting framework developed by Microsoft, optimizes GBDT for large datasets by using a histogram-based algorithm and depth-limited tree growth to enhance speed and efficiency. It incorporates Gradient-based One-Side Sampling (GOSS) to prioritize high-gradient data and Exclusive Feature Bundling (EFB) to reduce feature dimensionality, improving performance and memory efficiency (Gao et al., 2022). Once the best model is obtained, it is used to estimate labels for unlabeled tweets after feature extraction with TF-IDF, which converts text into numerical vectors. The machine-labeled data is then merged with human-labeled data to ensure consistency before visualizing the results using a word cloud (Samah et al., 2022).

RESULT AND ANALYSIS

Descriptive Statistics

Figure 3 shows that search interest using the "thrift clothes" query tended to increase from 2018 to 2023. Search trends fluctuated from 2018 to early 2023. The data shows that search interest was relatively stable at first but experienced a significant increase over time. The highest peak occurred in the first quarter of 2023, with GTI reaching 92, indicating very high interest in searches related to "thrift clothes" in that period. So, the increase in GTI indicates a growing public interest in thrift clothing.

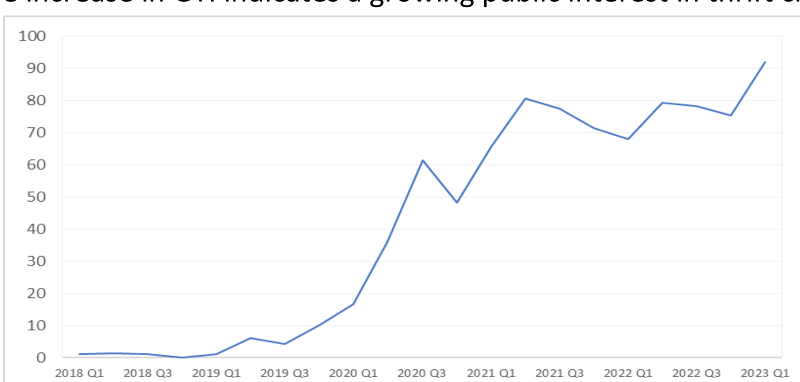

Figure 3. GTI with query “thrift clothes”
Source: Google Trend

Measurement Model

A statistical test was conducted to examine the impact of the Google Trend Index (GTI) and used clothing imports on the GDP of the textile and apparel industry subsector using the Autoregressive Distributed Lag (ARDL) method. Since ARDL requires variables to be stationary at the level or first difference, a unit root test was performed. Results indicate that while used clothing imports are stationary at the level, GTI and GDP became stationary only after first differencing, with probabilities of 0.0043 and 0.0298, respectively, both below the 5% significance threshold. As no variables were stationary at the second difference, the ARDL model is suitable for this study.

The ARDL model was constructed using a maximum lag of 4 for both the dependent and regressor variables. The best model, ARDL (3,4,4), was selected based on the AIC criterion, yielding an AIC of 13.38 and an Adjusted R-squared of 0.9897. This indicates that GTI and imported clothing explain 98.97% of GDP variations, with the remaining 1.03% influenced by unexamined factors. A cointegration test was conducted to assess long-term stability among variables using the bound test. The F-statistic of 50.36 exceeds the upper bound at the 5% level, confirming that the variables exhibit a long-term relationship. Thus, short-term estimates are obtained through the CointEq value, also known as the error correction term (ECT). The results indicate that the CointEq value (-1) is -0.39965 and is significant at the 5% level, confirming the existence of short-term cointegration in this model. Furthermore, the CointEq coefficient serves as a measure of the speed of adjustment, which reflects how quickly the model responds to changes. For the coefficient to be valid, it must be negative and statistically significant at the 5% level. Since the ARDL (3,4,4) model meets these conditions, it can be concluded that the model will reach equilibrium at an adjustment rate of 39.965% per quarter.

Table 2. Short Term Model

Variabel	Coefficient	Std Error	t-statistics	probability
D(PDB(-1))	0.4204	0.0497	8.4484	0.0035*
D(PDB(-2))	-0.6126	0.0447	-13.6978	0.0008*
D(GTI)	-56.9297	5.6771	-10.0279	0.0021*
D(GTI(-1))	-85.6341	5.1064	-16.7697	0.0005*
D(GTI(-2))	-43,6341	5.2200	-8.4171	0.0035*
D(GTI(-3))	-46.3471	5.0237	-9.2256	0.0027*
D(IMPORT)	-0.0006	0.0006	-1.0624	0.3660
D(IMPORT(-1))	0.0081	0.0007	10.8008	0.0017*
D(IMPORT(-2))	-0.0028	0.0007	-3.6738	0.0349*
D(IMPORT(-3))	0.0100	0.0009	10.7664	0.0017*
CointEq(-1)	-0.3996	0.0199	-20.0735	0.0003*

*significant at the 5% level
Source: Data processed by Eviews 12 (2023)

Table 2 presents the short-term model equation, where variables significant at the 5% level are marked with an asterisk (*). The ARDL modeling results indicate that GDP growth in the textile and apparel industry subsector is influenced by its past values. Specifically, GDP growth in the first lag has a significant positive effect, whereas in the second lag, it has a significant negative impact. A 1% increase in GDP two periods prior leads to a 0.61% decline in the current period's GDP. Additionally, the Google Trend Index (GTI) significantly affects GDP growth across multiple time periods. The current period, as well as the first, second, and third lags, all exhibit a negative impact on GDP growth in the textile and apparel industry subsector.

Similarly, the used clothing import variable has a significant impact in the first, second, and third lags. However, its effects vary across time. The first and third lags have a positive influence on GDP growth, while the second lag has a negative impact. Specifically, the coefficient for used clothing imports in the second lag is -0.00284, indicating that a 1% increase in used clothing imports results in a 0.00284% decrease in GDP for the textile and apparel industry subsector.

Table 3. LongTerm Model

Variabel	Coefficient	Std Error	t-statistics	probability
GTI	-53.3176	15.5308	-3.4330	0.0414*
|IMPORT|	-0.0305	0.01633	-1.8707	0.1581
C	40587.98	1750.76	23.1830	0.0002*

*significant at the 5% level
Source: Data processed by Eviews 12 (2023)

In the long-term model (Table 3), variables that are significant at the 5% level are marked with an asterisk (*). The GTI variable has a long-term influence on GDP growth in the textile and apparel industry subsector. A 1% increase in the Google Trend Index (GTI) related to thrift clothing is associated with a 53.31% decrease in the GDP of the textile and apparel industry subsector. Based on these findings, a model is formulated as shown in Equation (1).

$$\widehat{PDB}_t = 40587.9^* - 53.3176\, GTI_t^* - 0.03056\, IMPORT_t \quad (1)$$

To ensure the validity of the regression model, a classic assumption test was conducted. This includes tests for homoscedasticity and autocorrelation to verify that the underlying assumptions of the model are met. The Breusch-Pagan-Godfrey (BPG) test was applied to examine whether the data exhibits homoscedasticity. The null hypothesis (H_0) states that there is no heteroscedasticity, meaning the variance of the errors remains constant. The test results show a chi-square probability value of 0.6078, which is greater than the significance level of 5%. Consequently, H_0 fails to be rejected, providing sufficient evidence to conclude that the data meets the homoscedasticity assumption. Then, to assess whether the data is free from autocorrelation, the Run Test method was employed. The test results indicate a probability value of 0.4596, which exceeds the 5% significance level. As a result, H_0 fails to be rejected, suggesting no serial correlation in the data. This confirms that the non-autocorrelation assumption is satisfied.

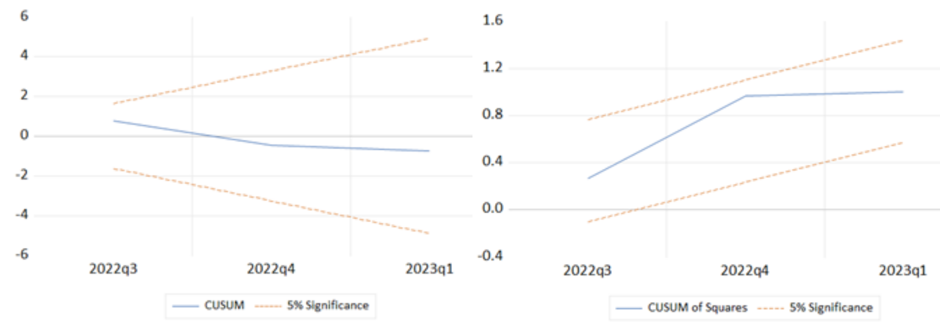

Figure 4. Stability Test of CUSUM & CUSUMQ Test Model Figure
Source: Data processed by Eviews 12 (2023)

After testing the classical assumptions, tests were carried out to check the stability of the model using CUSUM and CUSUMQ. The estimate is stable if the CUSUM and CUSUMQ plots do not exceed the upper and lower limits. As shown in Figure 4, both plots remain within the five percent significance line, represented by two straight red lines. Thus, it can be concluded that the estimated coefficients in the model are stable.

Sentiment Analysis

In addition to analyzing the economic impact using the ARDL model, it is also important to understand how public perception of thrifting can influence the textile sector. Therefore, sentiment analysis is conducted to examine patterns of public opinion that may contribute to the dynamics of industry. The incorporation of Sentiment Analysis enhances the robustness of this research. This aligns with the argument by Alita and Isnain (2020), who state that the impact and advantages of Sentiment Analysis contribute to the rapid development of related studies. The data was collected through web scraping techniques over a ten-day period, from May 20 to May 30, yielding a total of 880 tweets containing the keyword "thrift." Of these, 599 tweets were manually labeled based on human judgment, while the remaining 221 tweets were labeled automatically using machine learning.

As part of the process, text processing and feature extraction were performed using the TF-IDF method before developing a predictive model with a supervised learning approach. The supervised learning algorithm employed in this study is LightGBM. Once the model was constructed, its performance was evaluated by calculating the weighted accuracy, which accounts for class imbalances by assigning greater weight to the majority class.

Table 4. Accuracy Light GBM Model

Model	Weighted Accuracy	MAE	RMSE
Light GBM	0.79	0.175	0.389

Source: Data processed (2023)

As shown in Table 4, the model achieved a weighted accuracy of 79%, indicating its effectiveness in predicting unlabeled data. Additionally, the model demonstrated low MAE and RMSE values, further supporting its reliability. Therefore, the LightGBM-based model is considered suitable for estimating sentiment in unlabeled datasets.

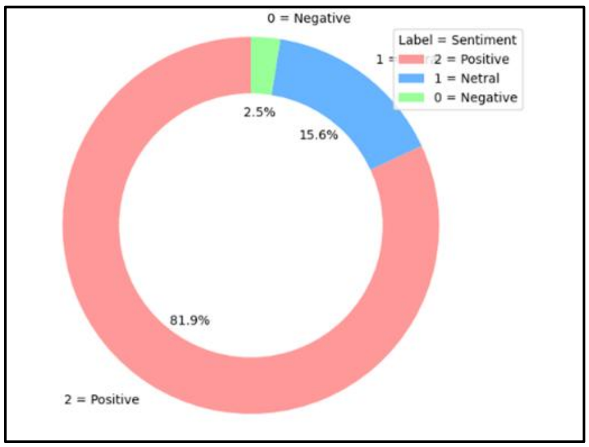

Figure 5. Merging Human Label Data and Machine Learning
Source: Data processed (2023)

The dataset consists of tweets labeled manually and those predicted using machine learning. Based on human labeling, 484 out of 599 tweets (80.80%) were classified as having positive sentiment, indicating that a majority of Indonesian Twitter users express approval or acceptance of thrifting. These sentiments are reflected in tweets containing expressions of preference for thrifted goods, participation in buying and selling second-hand items, and recommendations of thrifting to others. Similarly, as shown in Figure 5, after applying machine learning for sentiment classification, the predicted results exhibit a comparable trend, reinforcing the reliability of the model in capturing public sentiment. By merging human-labeled data with machine learning predictions, the analysis ensures consistency and scalability in sentiment assessment. The alignment between manually labeled data and machine-predicted sentiment highlights the model’s effectiveness in generalizing sentiment patterns across a larger dataset.

Figure 6. Visualization of Frequently Appearing Words in Positive Sentiment Tweets
Source: Data processed (2023)

The visualization of frequently appearing words in positive sentiment tweets, as shown in Figure 6, provides insights into the dominant themes within public discourse on thrifting in Indonesia. By identifying the most common terms, this analysis helps reveal user engagement patterns, preferred platforms, and the types of thrifted goods that are most discussed. The word cloud results indicate that Indonesian users actively participate in thrifting, either by buying or selling second-hand goods, primarily due to their affordability. The findings also highlight the widespread use of e-commerce platforms for thrift transactions. Additionally, the frequent appearance of clothing-related terms suggests that thrifted items in Indonesia predominantly consist of apparel, particularly those associated with vintage, coquette, and Korean fashion trends.

Discussion

The ARDL model results reveal a significant relationship between thrifting activities and the GDP of the textile and apparel industry, both in the short and long run. The analysis indicates that the rise of thrifting, predominantly driven by imported used clothing, negatively impacts the GDP growth of the textile and apparel sector. Specifically, short-term dynamics captured through the error correction term (ECT) suggest an adjustment speed of 38.6% per quarter, indicating that the industry gradually adapts to shocks caused by thrifting activities. This adjustment mechanism highlights the vulnerability of the textile and apparel sector to external pressures, particularly from the influx of imported used clothing, which poses a threat to local industries.

These findings align with previous research highlighting the negative impact of imported used clothing on local industries. For instance, Febrianti (2022) emphasized that

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the illegal importation of used clothing has led to a decline in demand for local textile products, ultimately resulting in the closure of several businesses. This phenomenon is further exacerbated by the fact that imported used clothing is often sold at significantly lower prices, making it more attractive to consumers and directly competing with local products. Similarly, Dewi et al. (2020) revealed that the sale of imported used clothing in Denpasar not only violates legal regulations but also has adverse effects on public health and the local economy. Furthermore, the negative impact of the Google Trend Index (GTI) on the GDP of this sector further amplifies the influence of thrifting. The increasing public interest in thrifting, particularly in imported used clothing, reflects a shift in consumer behavior that affects the performance of the textile and apparel industry. This trend not only impacts economic indicators but also disrupts the local business ecosystem. As highlighted by Siagian et al. (2023) the import of used clothing weakens the competitiveness of local products and results in significant economic losses for domestic textile entrepreneurs.

Moreover, the high public interest in thrifting is reinforced by sentiment analysis results, which indicate that 81.90% of tweets express positive sentiments toward thrifting. This finding aligns with the study by Firmansyah & Damayanti (2023), which reported 177 positive sentiments compared to 75 negative sentiments, demonstrating strong public acceptance of thrifting activities. These positive sentiments reflect a cultural shift in which thrifting is perceived as an affordable and fashionable alternative to purchasing new clothing, explaining the high demand for imported second-hand goods. However, the widespread enthusiasm for thrifting contrasts with its negative impact on the local textile industry, as highlighted in the previous discussion. This data underscores that the rise of thrifting is driven not only by economic factors but also by shifting consumer preferences.

The prohibition of used clothing imports, as stipulated in Minister of Trade and Cooperatives Decree No. 28 of 1982, aims to protect domestic industries, enhance the global competitiveness of Indonesian products, and safeguard consumer welfare. However, the prevalence of illegal imports underscores the need for stricter law enforcement and more effective supporting policies. To address this issue, policymakers and industry stakeholders must reinforce the enforcement of existing regulations, including imposing strict sanctions on illegal imports, while simultaneously enhancing the competitiveness of local products. Additionally, strengthening support for micro, small, and medium enterprises (MSMEs) in the textile sector is crucial by fostering greater public engagement in prioritizing and selecting domestically produced goods.

This study faces a significant limitation in its inability to capture data on illegal thrifting imports, which are not recorded in official statistics. As highlighted by Lomotey and Fisher (2006), the illegal trade of used clothing occurs both in exporting countries and regions such as Africa, creating a gap between official data and the actual situation. This limitation affects the accuracy of quantitative economic modeling, as observed in studies by Bigsten and Wicks (1996) and Frazer (2008), which may not fully capture the impact of the used clothing trade on local industries. To address this issue, future research should integrate additional variables that better capture thrifting activities and employ more advanced and robust statistical modeling. Furthermore, leveraging various social media platforms can provide a more comprehensive understanding of public sentiment toward thrifting.

CONCLUSION

This study concludes that thrifting negatively impacts the GDP of Indonesia's textile and apparel industry subsector. This effect is further evident in the high public interest in thrifting, which reflects strong demand for imported used clothing products. Consequently, the increasing influx of these imports continues to weaken the local textile industry, which faces challenges in competing on price and product appeal. To address this issue, stakeholders should strengthen the enforcement of existing regulations, including imposing strict sanctions on illegal imports, while enhancing the competitiveness of domestic products. Future research should incorporate additional variables that better capture thrifting activities and employ more advanced statistical modeling. Furthermore, leveraging various social media platforms can provide deeper insights into public sentiment toward thrifting.

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