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Integrating Explainable AI and the Kano Model to Derive Improvement Strategies for Essential Oils from Online Reviews

Akhdan Hanif Kartika Zaman *, Eko Liquiddanu

Department of Industrial Engineering, Universitas Sebelas Maret, Surakarta, 57126, Indonesia
* Corresponding Author: ekoliquiddanu@staff.uns.ac.id

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ABSTRACT

Growing consumer interest in natural wellness products, particularly essential oils, highlights the need to understand key quality product attributes affecting consumer satisfaction. In the digital era, customer reviews in marketplaces have become the main source of consumer-driven insights for improving production and service processes. However, conventional approaches often fail to systematically extract actionable insights from these unstructured data sources. This study proposes an integrated machine learning framework for three market on essential oils and their derivatives. This framework transforms thousands of online customer reviews into a structured analysis of satisfaction dimensions. The approach uniquely contributes by employing regression model combined with Explainable AI (SHAP) and KANO Classification to systematically applied based on SHAP insights to develop a marketing strategy based on three market segments for essential oil products and their derivatives. Eleven critical satisfaction dimensions were extracted, including aroma, price, packaging, delivery, and others. These segment-specific insights imply that producers should prioritize reliable pricing and delivery for low-tier markets, ensure strict price fairness and value consistency for mid-tier consumers, and, for high-tier segments, focus on integrating diffuser compatibility as a basic requirement while leveraging bonuses as emotional value-adds to enhance customer delight. Theoretically, this research introduces a scalable, Explainable AI-based approach for applying the Kano model to unstructured textual data, overcoming limitations of traditional survey methods. Despite its strengths, this study is limited by the absence of validation for the Kano categorization through survey-based procedures. Future work will address this limitation by conducting perception-based surveys or interviews to validate and refine the inferred categorizations. Nonetheless, this research contributes a methodology and provides actionable strategies for essential oil producers to align product improvements with consumer expectations in digital commerce environments.

1. Introduction

Essential oils have gained increasing popularity in recent years, driven by rising consumer interest in natural wellness, aromatherapy, and organic personal care (Sharmeen et al., 2021). Indonesia's export market has shown consistent growth over the last three years, with export values

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rising from approximately $826.7 million in 2022 to $842.8 million in 2023, and further increasing to $989.6 million in 2024 (Statistik, 2025). In Indonesia, especially in Central Java, this trend is reinforced by the country's rich biodiversity and traditional use of herbal extracts, positioning essential oils as a high-potential industry segment (Alighiri et al., 2017).

In parallel with market growth, the increasing role of e-commerce has transformed online marketplaces like Tokopedia into essential distribution channels for micro and small enterprises (IKM/UMKM). These platforms not only streamline transactions but also provide producers with direct access to a wider, digitally connected customer base. As online shopping becomes increasingly mainstream, consumer interaction is now mediated through digital interfaces where product reviews and ratings significantly shape purchasing decisions. The growing adoption of e-commerce in Indonesia offers both a commercial opportunity and a strategic advantage for producers seeking to understand and respond to customer needs more effectively.

One of the most valuable byproducts of digital marketplaces is the large volume of customer reviews. Online reviews could provide more information, insight, and even more efficient in cost to collect using data mining method (Qi et al., 2016). It inherently contains sentiment cues, both explicit and implicit that can be mined to reveal the dimensions shaping satisfaction or dissatisfaction. Online platform marketplace had reviews from customers of product they purchased that show satisfaction by the rating and written reviews given (Muthukumar & Kumar.J, 2024). Particularly in the context of e-commerce, where customer interaction is mediated through digital interfaces and reviews, there is a pressing need to understand which product attributes truly drive satisfaction or dissatisfaction (Zhang et al., 2023). Understanding online consumer behavior and offer practical insights for e-commerce companies could help adapt business models to better meet modern consumer expectation (Changchit & Klaus, 2020).

Despite of the market growth, most product development efforts still rely on internal assumptions, rather than systematically analyzing how consumers actually perceive various dimensions of product quality (Roberts & Darler, 2017). Studies on essential oils have focused on chemical composition, extraction methods, and packaging innovation, there remains a lack of empirical evidence on which product and service attributes are most valued by consumers, and how these attributes influence their overall satisfaction (Ju et al., 2022; Kholibrina & Aswandi, 2021; Muhammad et al., 2022). More critically, there is limited empirical evidence on which specific product, packaging, or service attributes are most valued by consumers, especially across different price segments. Moreover, although service quality is acknowledged as a key driver of satisfaction in general e-commerce contexts, its role within the essential oil industry remains underexplored (Hidayat et al., 2024; Suzer, 2022).

Traditionally, customer satisfaction has been assessed using survey-based methods such as SERVQUAL or QFD (Bahia et al., 2023; Niman, 2025; Santoso, 2006), are helpful but suffer from limitations from low scalability, high cost, and rigid constructs that may not fully reflect spontaneous from user in the digital age (Pournarakis et al., 2017). In contrast, customer reviews on e-commerce platforms provide unsolicited, real-time, and content-rich feedback, offering a promising alternative for understanding customer satisfaction (Davoodi et al., 2025). These reviews not only influence consumer purchase decisions but also serve as informal yet valuable reflections of satisfaction and user experience (Prasad Pattnaik, 2025). However, despite their potential, online reviews remain underutilized by businesses due to their unstructured format, linear presentation, poor searchability, and the relatively small proportion of insights buried in a large volume of text (Gundla & Otari, 2015).

Prior studies have explored various methods to analyze customer preferences and satisfaction from online reviews. Xiao et al., (2016) proposed a modified ordered choice econometric model combined with an extended Kano model to measure aggregate consumer preferences and categorize customer requirements using data extracted from Epinions.com. Bi et al., (2019) extracted customer satisfaction dimensions via latent dirichlet allocation (LDA) and sentiment orientations through support vector machines, then modeled satisfaction effects using an ensemble neural network alongside an effect-based Kano model. Park & Jeon (2022) enhanced sentiment analysis by incorporating sentiment strength with an LSTM+GRU ensemble and applied multivariate regression alongside Kano model-based rules to identify customer requirements considering customer background and product evolution. (Adak et al., 2022) utilized deep learning models including LSTM and Bi-GRU-LSTM-CNN for sentiment analysis on food delivery service reviews and employed explainable AI techniques, SHAP and LIME, to interpret model predictions and identify key factors influencing customer sentiment.

To bridge the gap between consumer satisfaction analysis and practical product improvement in the essential oil industry, this study proposes a comprehensive and scalable framework that transforms unstructured customer reviews into strategic insights. Specifically, the research aims to extract and categorize customer satisfaction dimensions (CSDs) from online reviews, and translate these insights into actionable recommendations for different market segments.

This study introduces a novel framework that leverages BER Topic for advanced topic extraction Hong Liao (2025) within the Indonesian e-commerce context, large language models (LLMs) for stable sentiment analysis and extract fine-grained insights from text data (Ghatora et al., 2024; Maarif, 2022; Upadhye, 2024). While Kano model has long served as a valuable tool for categorizing product attributes into must-be, performance, and excitement factors that influence satisfaction, traditional applications rely heavily on structured survey data, limiting scalability and adaptability in dynamic digital environments. SHAP (SHapley Additive Explanations) used to quantify the influence of each satisfaction dimension on consumer ratings and systematically classified into kano classification (Kametani et al., 2010; Kano et al., 1996).

This research presents a methodological unified pipeline for analyzing unstructured essential oil product reviews and suggest strategy to upcome most contributing customer satisfaction dimension from topic modeling result to identify customer satisfaction. This study presents an end-to-end framework that connects each analytical step into a Kano-based quality improvement mapping, specifically tailored to essential oil products. Operationalizing Kano classification criteria using SHAP attribution values provide a data-driven alternative to traditional survey-based Kano questionnaires, which enhances scalability and objectivity. Practically, the study provides actionable insights by identifying and quantifying the most influential CSDs that are uniquely relevant to essential oil products. By applying this integrated methodology to online reviews of essential oil products, the study aims to uncover key drivers of consumer satisfaction directly from user-generated content.

2. Method

2.1. Research Framework

This study proposes a quantitative framework to analyze consumer satisfaction by transforming unstructured online reviews into strategic insights. As seen in Fig. 1, the primary focus of this study is on analyzing consumer satisfaction with essential oil products within the e-commerce context, utilizing an integrated approach of Natural Language Processing (NLP) and Explainable AI (XAI) to formulate product improvement strategies. The framework used in this research consists of four keys:

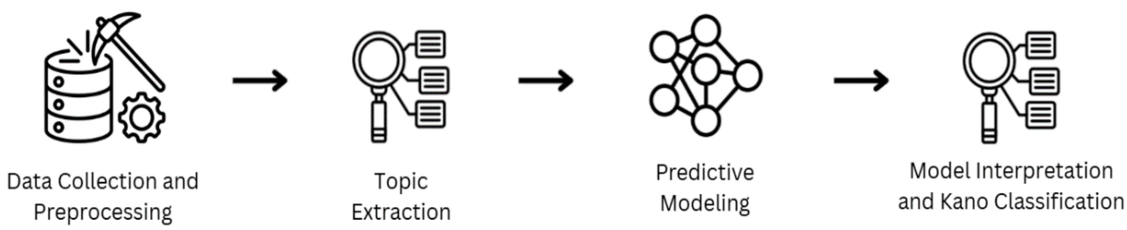

Fig. 1. Research Framework. Primary focus of this study is on analyzing consumer satisfaction with essential oil products within the e-commerce context

2.2. Data Collection

The initial stage involves systematically capturing the Voice of the Customer (VOC) regarding essential oil products. To obtain a representative corpus of consumer feedback on essential-oil products sold via Tokopedia, we extracted 35,000 publicly available reviews from January 2018 to February 2025. Reviews were collected through an automated Python pipeline that employed Selenium to navigate the marketplace's dynamic webpages and Beautiful Soup to parse the underlying HTML. After acquisition, the raw data underwent a multi-stage preprocessing workflow. First, exact duplicates were eliminated to ensure the independence of observations. Next, algorithmically detected boilerplate and bot-generated remarks, such as single-phrase endorsements ("good product"), were removed, alongside any review comprising fewer than three words, thereby retaining only substantive user contributions.

Finally, the cleaned corpus was stratified into three price-based cohorts to facilitate tier-specific analyses: (a) Low-price products (< IDR 50.000), (b) Mid-price products (IDR 50.000–150.000), (c) High-price products (> IDR 150.000). This segmentation enables comparative assessments of consumer sentiment across distinct pricing brackets and validated with significancy test using Kruskal-Wallis test. The final dataset of 23.068 reviews was derived from an initial pool of 35,000+ entries after cleaning and filtering steps to remove noise, spam, and duplicates, also removing reviews with fewer than three words, as such entries typically lack substantive content.

2.3. Topic Extraction

To systematically identify which product and service attributes customers value most, this framework employs BER Topic. To distil the corpus into actionable customer-satisfaction dimensions (CSDs), BER Topic were applied. BER Topic combines transformer embeddings with density-based clustering, enabling it to capture semantic subtleties that classical topic modeling often misses (Mutsaddi et al., 2025). Sentence-level representations were generated with the paraphrase-multilingual-MiniLM-L12-v2 encoder, the resulting embeddings were clustered by HDBSCAN, which adaptively determines cluster density without requiring a predefined topic count. For each emergent cluster, salient terms were extracted using class-based TF-IDF, producing an initial set of 600 granular topics.

Two researchers independently reviewed and inductively merged these topics, guided by established essential-oil attributes such as aroma, perceived efficacy, and packaging quality, into eleven higher-order CSDs. Ambiguous cases, for example distinguishing "packaging" from "shipping condition," were resolved through consensus with domain experts, thereby ensuring conceptual clarity and content validity. The 11 consolidated CSDs served as structured input features for sentiment labeling and regression modeling. Each CSD was operationally defined through its constituent BER Topic keywords (e.g., 'Aroma' = {Wangi, Bau, Aroma}), ensuring semantic consistency during downstream analysis.

2.4. Predictive Modeling

In the predictive modeling stage, we quantified how each customer-satisfaction dimension (CSD) influences the one-to-five-star ratings in the Tokopedia dataset. Each review was first tagged as positive or negative for every CSD using GPT-4o-mini. The text labels were then converted into numerical features by one-hot encoding every CSD sentiment pair, for example "Aroma_POS" or "Price_NEG". This binary matrix preserves categorical information while making the data suitable for regression algorithms. Five learning algorithms were evaluated: Linear Regression, Random Forest, Support Vector Regression, Gradient Boosting, and XGBoost. An exhaustive grid search tuned hyperparameters for each model while minimizing mean absolute error, root mean squared error, and maximizing R^2.

2.5. Model Interpretation and Kano Classification

In the final stage, we categorized each customer satisfaction dimension (CSD) into one of Kano's categories: Must-be, Performance, or Excitement. This was done using threshold-based interpretations of SHAP values, based on the method by (Park & Jeon, 2022). The median SHAP values separately for positive and negative mentions of each CSD in Eq. (1).

$$\varphi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \quad (1)$$

As seen in Fig, 2, to interpret the model, we applied SHAP (Shapley Additive Explanations). For any feature i, the SHAP value represents the average marginal contribution that the feature adds across all possible subsets S of the full feature set N. A positive φ_i indicates that the feature tends to raise the predicted rating, while a negative value pulls it downward. Ranking these values reveals both the direction and magnitude of each CSD's impact, giving industrial engineers clear, quantifiable levers for product or service improvement. Median SHAP values for each CSD-sentiment pair were then computed to enable robust Kano classification.

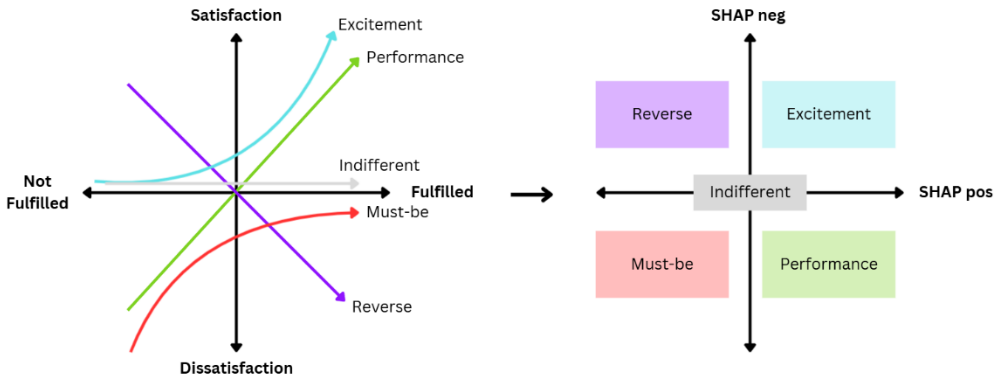

Fig. 2. Kano Classification. A CSD was classified as Must-be if $SHAP_{neg} < 0$ and $SHAP_{pos} < 0$. It was categorized as Performance when $SHAP_{neg} < 0$ and $SHAP_{pos} > 0$. A CSD was labeled as Excitement when $SHAP_{neg} > 0$ and $SHAP_{pos} > 0$. Reverse is the condition when $SHAP_{neg} > 0$ and $SHAP_{pos} < 0$.

3. Results and Discussion

3.1. Data Collection and Preprocessing

Based on the Table 1, it can be seen that a total of 23.068 review data points were successfully collected from the Tokopedia site, provided by customers for a product after they received it. The reviews with a rating of 1 totaled 302, with a rating of 2 totaled 202, with a rating of 3 totaled 574, with a rating of 4 totaled 1.248, and the highest rating reached 20.742. The preprocessed dataset comprised 23.068 validated reviews stratified across price segments which is low-tier (15.0%, n=3.448), mid-tier (75.5%, n=17.402), and high-tier (9.6%, n=2.218).

Table 1. Data Collection Result

Rating	Review Count by Segment			
	Low	Mid	High	Total
1	76	214	12	302
2	48	145	9	202
3	123	413	38	574
4	237	929	82	1.248
5	2.964	15.701	2.077	20.742
Total	3.448	17.402	2.218	23.068

In many cases, a bimodal or J-shaped distribution of ratings, as seen above, is commonly observed in customer satisfaction studies. This distribution does not require special treatment for data imbalance cases because the main focus of this study is to measure the contribution or effect of customer satisfaction dimensions. However, this study requires a prediction model that does not rely on the assumption of normal distribution and is capable of capturing non-linear relationships among the CSD dimensions.

3.2. Identification of Customer Satisfaction Dimensions (CSDs)

This section explains the results of identifying the main themes from the reviews that will be used as Customer Satisfaction Dimensions (CSD). As seen in Table 2, topic extraction was performed using Python with the help of the BER Topic library and the BERT embedding model, specifically paraphrase-multilingual-MiniLM-L12-v2. Initially, 600 topics were extracted from 23.068 reviews. 11 topics were found from similarity and same meanings.

Table 2. Identified Topic as CSD

No	CSD	Freq	No	CSD	Freq
1	Aroma	8441	7	Content Quality	2306
2	Bonus	820	8	Efficacy	284
3	Price	321	9	Service	1742
4	Packaging	2371	10	Delivery	155
5	Descirption Conformance	813	11	Humidifier Application	249
6	Shipping Condition	656			

The topic extraction using the BER Topic method resulted in the identification of 11 distinct themes, which were then consolidated into Customer Satisfaction Dimensions (CSDs). These dimensions emerged from the recurring patterns within the customer reviews and reflect attributes that consumers most frequently mention in relation to their experiences with essential oil products. Aroma appeared as the most dominant theme, indicating that scent plays a central role in shaping customer satisfaction. Mentions of bonus items suggest that additional offerings, such as free gifts or bundled products, are perceived as added value by customers. Price frequently appeared in both positive and negative contexts, signaling its importance in purchase decisions and perceived fairness.

Packaging was often highlighted, reflecting consumer attention to product presentation and protective quality. Description conformance relates to the alignment between advertised and received products, which shapes customer trust. Mentions of shipping condition suggest concern with delivery handling and physical integrity. Content quality and efficacy both reflect perceived product performance, particularly regarding the consistency and effectiveness of the oils. References to customer service indicate that post-purchase support remains a key satisfaction factor, while mentions of humidifier compatibility reflect evolving consumer behavior in integrating essential oils with devices. Collectively, these dimensions represent the most salient and relevant aspects of customer satisfaction as naturally expressed through user-generated content, revealing areas with the greatest influence on consumer perception. The output of topic extraction via BER Topic formed the basis of CSDs, which were then used in SHAP-enabled regression modeling to quantify satisfaction impact and subsequently fed into Kano classification logic.

3.3. Prediction Modeling

To quantitatively assess the influence of each Customer Satisfaction Dimension (CSD) on consumer ratings, a predictive modeling process was conducted. This stage resulted sentiment label, predictive model, and interpretation through Explainable AI, forming the analytical foundation for Kano classification.

3.3.1. Sentiment Labeling

The findings show that Aroma is the most influential dimension, with the highest number of positive reviews, particularly in the 5-star category, while negative sentiment is seen in lower ratings. As seen in Fig. 3, Price and Quality dimensions are associated with dissatisfaction, as indicated by the higher number of negative reviews in the 1 and 2-star ratings. Packaging and Description Accuracy receive generally positive feedback, especially in higher ratings. Meanwhile, Bonus and Humidifier Application have fewer positive reviews, suggesting they are less important to customer satisfaction. Overall, aroma and packaging are key drivers of satisfaction, while price and quality issues lead to dissatisfaction.

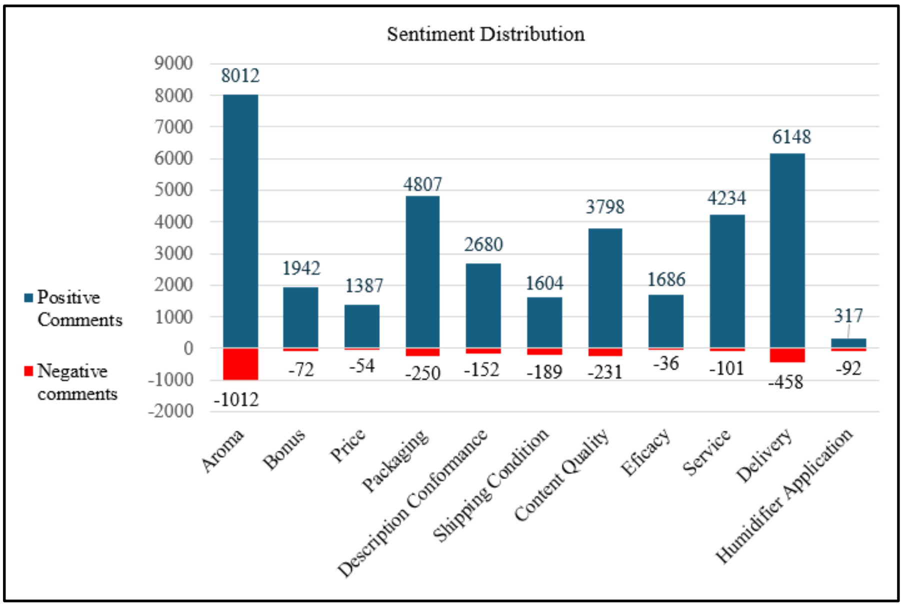

Fig. 3. Sentiment Distribution. Price and Quality dimensions are associated with dissatisfaction, as indicated by the higher number of negative reviews in the 1 and 2-star ratings

To assess the quality and reliability of sentiment labeling, a Cohen's Kappa (κ) agreement test was conducted between the LLM-generated sentiment classifications and human annotations on a random sample of 200 reviews.

Table 3. Cohen's Kappa Confusion Matrix

Confusion Matrix		Validator			
		-1	**0**	**1**	**Total**
LLM	-1	5	4	0	9
	0	0	619	24	643
	1	0	31	125	156
	Total	5	654	149	808

The resulting κ value = 0.77 indicates substantial agreement, based on the Landis and Koch (1977) interpretation scale, thereby validating the consistency of the automated labeling. As seen in Table 3, the confusion matrix illustrates that the majority of samples (619 out of 808) were correctly labeled as neutral by both the LLM and human annotators. Minor disagreements are observed in the misclassification of 31 reviews where the LLM predicted positive sentiment while the human labeled them as neutral, and 24 cases of neutral misclassified as positive. Negative sentiment classes exhibited stronger agreement, with only minimal discrepancies. This result confirms that the labeling process maintains a high level of accuracy and can be reliably used for downstream modeling and SHAP-based analysis.

3.3.2. Prediction Model

The XGBoost Regressor model achieved the lowest MAE values across the training, validation, and test datasets, with scores of 0.1284, 0.1354, and 0.1251, respectively. This performance indicates that XGBoost excels in making accurate predictions by minimizing absolute errors compared to other models. As seen in Table 4, a lower MAE indicates better prediction accuracy, making it a key indicator in evaluating the performance of predictive models on user data. Additionally, research on pricing strategies in e-commerce has found that models with an MAE between 0.126 and 0.130 are considered to demonstrate strong predictive performance (Chowdhury et al., 2024). The RMSE value in this study (0.46) is slightly higher than previous research Park & Jeon (2022), it remains within an acceptable range, especially considering the unstructured and linguistically diverse nature of consumer reviews.

Table 4. Prediction Model Evaluation

Model	MAE			RMSE			R^2		
	Train	Val	Test	Train	Val	Test	Train	Val	Test
Linear Regression	0.202	0.202	0.196	0.461	0.447	0.435	0.373	0.456	0.412
Random Forest	0.178	0.187	0.174	0.436	0.455	0.417	0.442	0.436	0.461
SVR	0.205	0.216	0.205	0.445	0.470	0.431	0.418	0.400	0.422
Gradient Boosting Regressor	0.173	0.186	0.174	0.429	0.454	0.417	0.457	0.439	0.461
XGBoost Regressor	0.128	0.135	0.125	0.459	0.462	0.441	0.379	0.421	0.396

Although the R^2 value on the test data is slightly lower than that of Random Forest and Gradient Boosting, the main focus of this study is to achieve precise predictions at the individual review level, rather than explaining the overall variance in the data. R^2 values below 0.6 are generally considered suboptimal for machine learning models (Black & Babin, 2019; Wiesner et al., 2014). However, in the context of social data such as customer reviews, which are inherently noisy and subjective, a relatively low R^2 value remains acceptable and meaningful (Newman & Newman, 2000; Qi et al., 2016). R^2 values between 0.3–0.5 are typical due to variance in human perception and language ambiguity. Therefore, XGBoost Regressor is selected as the best model for further analysis using Explainable AI, as it provides more accurate predictive estimates and allows for a detailed interpretation of feature contributions.

3.4. Model Interpretation and Kano Classification

SHAP values quantitatively linked CSDs to satisfaction outcomes, confirming methodological coherence: Topics identified by BER Topic (e.g., 'Humidifier Application') directly manifested as high-impact features in regression. Their directional effects enabled unambiguous Kano mapping per predefined thresholds. From the explainer calculation, the median SHAP value is calculated for each active feature as a representation of the strength and direction of the feature's influence in aggregate. The median SHAP values of the CSD features are shown in the following Table 4.

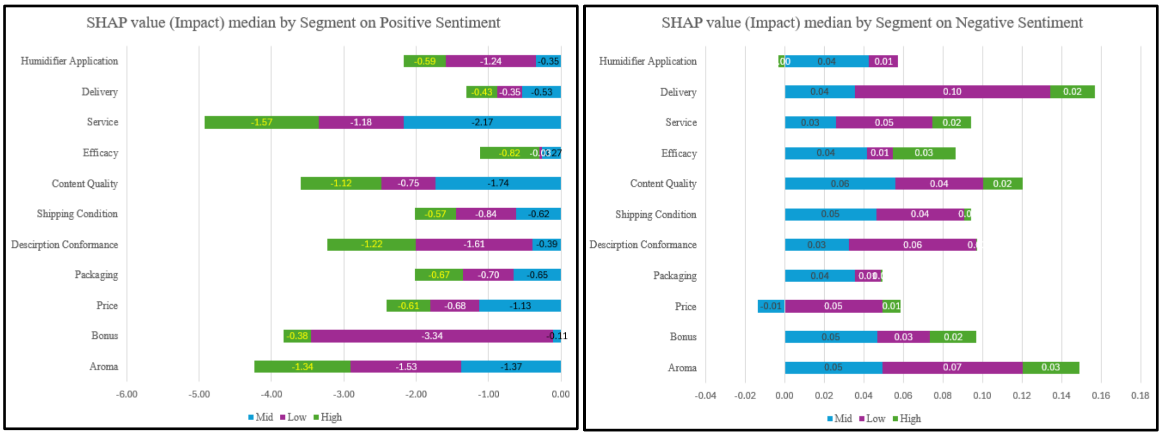

Fig. 4. SHAP Value Median by Segment (a) on Positive Sentiment (b) on Negative Sentiment

From the classification results, most customer satisfaction dimensions (CSDs) of essential oil products were categorized as Performance attributes across all price segments. As seen in Table 5, this dominance of the Performance category can be attributed to biases in customer reviews, specifically under-reporting and purchasing biases, where consumers typically provide reviews predominantly when experiencing highly satisfactory or unsatisfactory outcomes related to clearly functional. Consequently, foundational or exciting features may remain underrepresented, as consumers often overlook or fail to explicitly mention their absence.

Table 5. Kano Classification from SHAP Values

Customer Satisfaction Dimension	Kano Classification by Segment		
	Low	Mid	High
Aroma	P	P	P
Bonus	P	P	P
Price	P	M	P
Packaging	P	P	P
Descirption Conformance	P	P	P
Shipping Condition	P	P	P
Content Quality	P	P	P
Efficacy	P	P	P
Service	P	P	P
Delivery	P	P	P
Humidifier/Diffuser Application	P	P	M

*P: Performance; M: Must-be

Nevertheless, the explainable AI results indicated that certain segments had explicit basic expectations for specific features. Thus, segment-specific analysis of each CSD dimension is essential to distinguish attributes that consumers genuinely perceive as critical, emotionally differentiating, or merely supplementary. This targeted insight allows SMEs to develop more precise quality improvement strategies, grounded in a comprehensive understanding of service attributes genuinely valued by consumers in each segment. A Kruskal–Wallis H test was conducted to assess whether the impact of price on customer satisfaction which measured by SHAP values for both positive and negative sentiments differed across price-based customer segments (low, mid, and high).

Table 6. Kruskal-Wallis H Test on Price

Sentiment Dimension	Test Statistic (χ^2)	df	N	Asymptotic Sig. (p-value)
Price – Positive Sentiment (csd3_0)	6,850.06	2	23,068	< 0.001
Price – Negative Sentiment (csd3_1)	10,060.54	2	23,068	< 0.001

As seen in Table 6, for positive sentiment (csd3_0), the test revealed a statistically significant difference in SHAP value distributions across segments, χ^2 (2) = 6850.06, $p < 0.001$. For negative sentiment (csd3_1), the test also indicated a significant difference, with a higher test statistic value, $\chi^2(2) = 10060.54$, $p < 0.001$. These results suggest that both positive and negative perceptions of price vary significantly between market segments, and that negative sentiment exhibits even greater variation, implying that pricing dissatisfaction may be a more polarizing factor among consumer groups than satisfaction.

3.4.1. Low-Price Segment Implication

In the economical price segment, Kano classification results indicated that all Customer Satisfaction Dimensions (CSDs) fell within the Performance quadrant. This demonstrates that consumers in this segment predominantly have functional, linear expectations towards product attributes. Features such as price, delivery, aroma, quality, service, and benefits directly enhanced customer satisfaction when present and decreased satisfaction when absent, highlighting that consumer closely associate their positive experiences with tangible, measurable product performance. This tendency also implies that economical segment customers do not hold high expectations for additional or supplementary features, considering them merely as basic performance elements whose absence is tolerable without significantly lowering their baseline satisfaction (Astuti & Bahrun, 2022).

However, certain dimensions, notably delivery and efficacy, were observed to approach the Excitement quadrant closely, suggesting that consumers in this segment are beginning to develop latent expectations for superior experiences, even without explicitly demanding them. For instance, inadequate delivery minimally decreased satisfaction but notably increased satisfaction when performed exceptionally. Thus, these attributes can serve as latent Excitement attributes, enabling SMEs to strategically differentiate their products without incurring substantial production costs. Simple initiatives such as improving packaging, providing transparent tracking information, or offering volume-based pricing adjustments can significantly enhance customer satisfaction, potentially fostering long-term loyalty and positive brand perception (Sardar et al., 2024).

3.4.2. Mid-Price Segment Implication

In the medium-priced segment, Kano classification showed that the majority of Customer Satisfaction Dimensions (CSDs) fell within the Performance quadrant, indicating that consumers in this segment evaluated essential oil product features primarily based on functionality and proportional impact. Attributes such as aroma, benefits, quality, packaging, delivery, customer service, and diffuser application positively influenced satisfaction when present and negatively impacted satisfaction when absent, reflecting stable and well-defined expectations regarding these core features (Lis-Balchin, 1997).

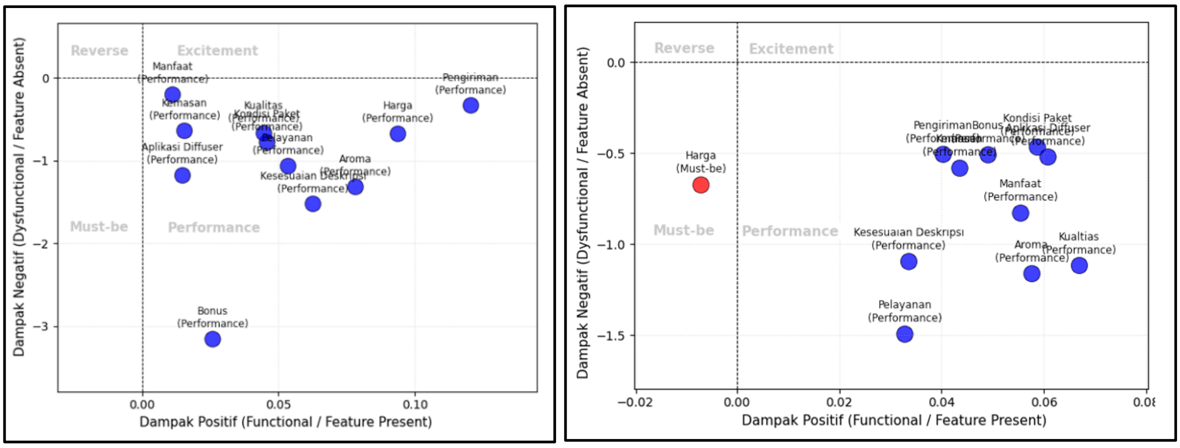

Fig. 5. Kano Plot (a) Low-Price Segment; (b) Mid-Price Segment.

As seen in Fig. 5, the price dimension was uniquely categorized as Must-be in this segment, signifying heightened price sensitivity among mid-tier consumers; discrepancies from expected pricing directly caused dissatisfaction, whereas alignment or lower prices did not substantially increase satisfaction (Kaewpetch et al., 2023). While no features distinctly approached the Excitement or Reverse quadrants, customer service and quality attributes notably demonstrated strong Performance characteristics, substantially affecting satisfaction positively when delivered well and negatively if performed poorly. Overall, this perception pattern highlights that medium-segment customers are transitioning from purely functional expectations toward seeking added experiential value. Consequently, businesses targeting this segment should maintain rigorous quality standards while exploring small-scale innovations like product sampling, attractive packaging, or engaging unboxing experiences, ultimately nurturing customer loyalty through exceeded expectations.

3.4.3. High-Price Segment Implication

In the premium price segment, Kano classification results indicated that most Customer Satisfaction Dimensions (CSDs) remained within the Performance quadrant, suggesting that premium consumers still primarily evaluate essential oil product features based on functional performance, significantly impacting satisfaction positively when present and negatively when absent. As seen in Fig. 6, Attributes such as product benefits, delivery, bonuses, aroma, quality, and customer service exhibited strong impacts, reflecting the heightened standards and more extreme responses of premium consumers toward product experiences. Notably, the Diffuser Application dimension consistently appeared as a Must-be attribute, highlighting that premium consumer perceive technological support as a fundamental expectation rather than merely a value-added feature.

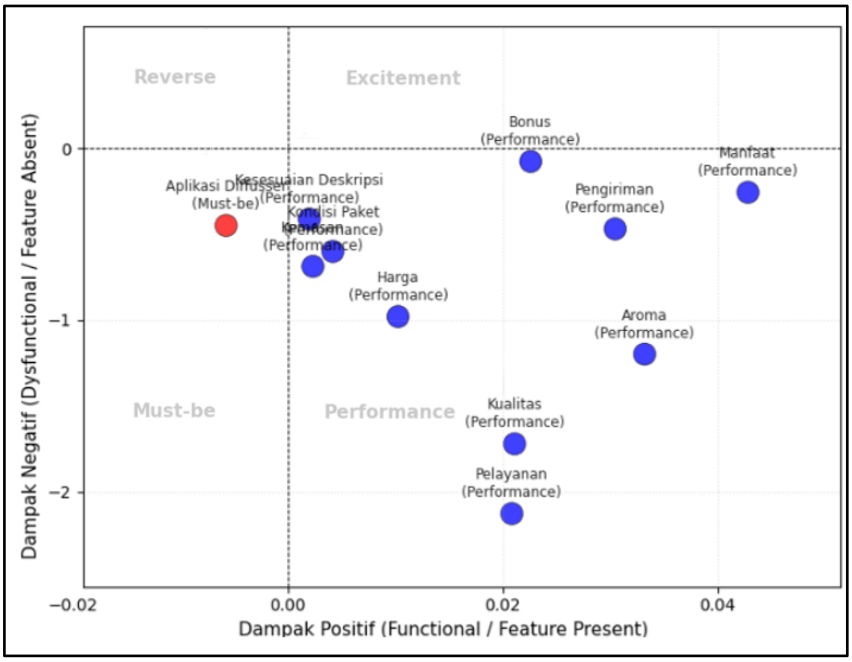

Fig. 6. Kano Plot High-Price Segment. Attributes such as product benefits, delivery, bonuses, aroma, quality, and customer service exhibited strong impacts

Moreover, several other attributes like Product Description Accuracy, Package Condition, and Packaging also approached the Must-be quadrant, emphasizing that their absence significantly reduced satisfaction more than their presence enhanced it. Meanwhile, attributes like Bonus and Product Benefits approached the Excitement quadrant, suggesting premium consumers highly appreciate surprise elements and additional features enhancing emotional value and exclusivity, without significant dissatisfaction if absent. Consequently, SMEs targeting premium segments should prioritize consistently meeting Must-be expectations and strategically leverage Excitement attributes to enhance customer experiences through technological integration, personalized bonuses, superior packaging, and after-sales support, thereby fostering long-term loyalty and heightened customer satisfaction

Overall, the three price segments share similarities in their perception of core attributes such as aroma, service, and quality, which are consistently classified as Performance attributes and directly contribute to customer satisfaction. Strategic differences emerge in certain segment-specific attributes. In the low-price segment, all dimensions are classified as Performance attributes, indicating linear and functional expectations. However, Bonus shows a strong negative impact when poorly delivered, while Delivery contributes the most to satisfaction when performed well. The mid-tier segment exhibits high price sensitivity, with price classified as a Must-be attribute, demanding consistent value and price fairness as non-negotiable requirements. Meanwhile, the high-price segment reflects more complex baseline expectations, where diffuser compatibility is categorized as a Must-be attribute. Bonus and Efficacy approach the Excitement quadrant, while Description Conformance, Shipping Condition, and Packaging are close to the Must-be region, indicating rising consumer sensitivity toward basic reliability features.

This study makes a novel contribution by being the first to operationalize SHAP-based Kano classification specifically within the context of essential oils from Indonesian e-commerce reviews. It also uniquely revealing how customer satisfaction dimensions (CSDs) exhibit segment-specific impact patterns through data-driven attribution. By bridging machine learning outputs with strategic quality frameworks, this research enhances both theoretical understanding and applied innovation in digital-era customer satisfaction analysis.

Despite its contributions, the study presents several limitations. First, the exclusive use of e-commerce reviews limits the generalizability of findings to alternative platforms, where user behavior and expectations may differ. Second, while SHAP-based thresholds offer a scalable categorization method, the inferred Kano classifications require validation through perception-based approaches, such as conjoint analysis or structured Kano surveys.

4. Conclusion

This study successfully addresses the gap in understanding consumer priorities for essential oil products in the Indonesian e-commerce market by extracting and classifying customer satisfaction dimensions (CSDs) from online reviews to provide actionable, segment-specific improvement strategies. Theoretically, this research contributes by empirically demonstrating the dynamic nature of customer requirements for essential oil products, showing how the classification of attributes shifts from being performance enhancers to basic expectations across different market segments. The classification of customer satisfaction dimensions (CSDs) using the Kano model revealed that most aspects, such as aroma consistency, packaging reliability, description accuracy, package condition, product quality, service, and delivery, function as Performance attributes, where incremental improvements directly boost satisfaction, while price and diffuser-app integration emerged as Must-be attributes whose absence immediately undermines customer trust. Building on these insights, this research recommend that producers maintain competitive, value-aligned pricing as a non-negotiable baseline, continuously refine aroma formulation and descriptive accuracy to align consumer expectation with experience, strengthen packaging and logistics processes to prevent fulfillment failures, and for premium segments, ensure robust diffuser support and introduce selective value-added bonuses to generate “wow” effects. Methodologically, this research advances the field by demonstrating how Explainable AI can bridge predictive modeling and actionable quality management, offering both theoretical contribution and operational relevance in data-rich consumer industries. Although this study introduces a novel SHAP-based Kano pipeline, it acknowledges the need for direct validation future work should integrate perception-based Kano surveys and mixed-method approaches to triangulate and further refine the SHAP-inferred categorizations.

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