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Analyzing Influence Factors of Jewelry Products Purchasing in Online Marketplaces Using Natural Language Processing

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Abstract. This independent study aims to analyze the factors influencing online jewelry purchasing decisions based on the 7Ps marketing mix framework, utilizing Natural Language Processing (NLP) and Machine Learning techniques. The dataset comprises 5,766 user reviews scraped from Shopee and Lazada. The research followed the CRISP-DM standard, employing TF-IDF for vectorization and Proportional SMOTE for data balancing to preserve the original significance of the factors. Comparative performance results revealed that the XGBoost algorithm achieved the highest accuracy at 75.39% and an F1-score of 75.30%. Meanwhile, the WangchanBERTa model, fine-tuned for 20 epochs, reached an accuracy of 74.09%, hindered by data volume constraints and Out-of-Vocabulary (OOV) issues. However, the Random Forest Classifier yielded the highest ROC AUC at 93.73%, demonstrating superior class differentiation capabilities. The findings indicate that the most discussed factors are Product (33.37%) and Process (24.19%), with "aesthetic design" and "shipping speed" identified as critical drivers of maximum customer satisfaction. These insights assist entrepreneurs in strategic marketing planning, inventory management, and packaging development to sustainably enhance competitiveness in the online marketplace.

Keywords: Natural Language Processing, 7P's Marketing Mix, Machine Learning.

1 Introduction

Marketing is defined as the business activities that facilitate the flow of goods and services to consumers, ensuring that their needs and satisfaction are met. It plays a pivotal role in a nation's economic growth and development. Currently, the gem and jewelry industry is one of Thailand's top ten export sectors, generating significant national revenue.

In 2019, prior to the COVID-19 pandemic, Thailand's exports of gems and jewelry (excluding unwrought gold) were valued at 8,095.65 million USD, a 6.34% increase [1]. In 2020, while the export growth rate stood at 15.94%, imports plummeted by 33.51%, and imports excluding unwrought gold dropped by 40.09% due to the pandemic's impact [2]. By 2021, export values for these items reached 6,158.66 million

USD, reflecting a 26.94% recovery [3], with continued growth projected for 2022 as pandemic restrictions eased [4].

By 2022, the export growth rate for gems and jewelry, including gold, surged by 50.89%, while the growth rate excluding gold rose by 48.16% compared to 2021. Unwrought gold ranked as the second-largest export product (24.39%), followed by diamonds (18.00%), colored stones (11.62%), and imitation jewelry (3.58%).

In 2025, the industry ascended to become Thailand's third-largest export category, accounting for approximately 8% of the country's total export value. From January to November 2025, export value soared to approximately 24,754.20 million USD, a growth of over 46% year-on-year [19]. Despite this remarkable growth, projections for 2026 suggest a slight slowdown due to external factors, such as the import tax policies of key partners like the United States and global gold price volatility. Consequently, entrepreneurs must pivot toward emerging trends, specifically "Sustainable Jewelry," such as lab-grown diamonds. This shift aligns with Environmental, Social, and Governance (ESG) principles and the evolving preferences of modern consumers who prioritize ethics and environmental impact alongside aesthetics [20]

Technological advancements, particularly the internet, have deeply integrated into daily life, transforming communication, transactions, entertainment, and commerce. According to Nukulsompratana (2026) in "Global Online Shopping Behavior in 2026" [5], 61.7% of the global population aged 25–54 purchase goods and services online. Notably, Thailand ranks second globally in online shopping frequency at 68.6%. Key drivers for online purchases include free shipping (50.7%), discount coupons (38.9%), and customer reviews (32.2%). The convenience and accessibility of e-commerce platforms have fundamentally shifted consumer behavior toward online channels.

Fig. 1. Weekly Online Shopping by Country 2025. [5].

Previous research by Muangtum (2021) utilized customer insight data for Alepa through the "Block Wish" campaign [6]. By collecting and analyzing unstructured data from Facebook messages, the study identified high-demand products, allowing businesses to make data-driven investment decisions that successfully boosted sales. This demonstrates the efficacy of leveraging consumer insights for business expansion.and 4969.55 million U.S. dollars in 2020, with an average annual growth In the contemporary market, minerals and gemstones are increasingly fashioned into everyday wearable jewelry and amulets, such as rings, bracelets, and necklaces. Beyond their aesthetic and spiritual value, they serve as symbols of social status.

This study aims to investigate the factors influencing the online purchase of gem and jewelry products by extracting consumer reviews from major e-commerce platforms, specifically Shopee and Lazada. Unlike previous studies [13][14] that primarily relied on questionnaires—which may be limited in capturing real-time, in-depth sentiments—this research addresses a significant gap by applying Natural Language Processing (NLP) techniques to analyze unstructured review data.

This approach offers a theoretical contribution by integrating Data Science with marketing theories. Furthermore, it provides a practical contribution for jewelry entrepreneurs by identifying consumer expectations within the 7P's marketing mix framework for e-commerce, ultimately aiding in strategic investment, operational planning, and sales optimization.

2 Literature Review

2.1 Natural language processing

Natural Language Processing (NLP) is a field of study focused on enabling computers to understand and interpret human communication in various forms, including text, speech, and imagery. By integrating computer science with linguistics, NLP allows machines to compute and derive meaning from human language. The process typically involves Text Preprocessing to prepare raw data for analysis. Key techniques include sentence segmentation, word tokenization, lemmatization or stemming, the removal of stop words, and the creation of word representations such as Bag-of-Words or TF-IDF vectors. Furthermore, advanced linguistic analysis involves Part-of-Speech (POS) tagging and Named Entity Recognition (NER) to identify grammatical structures and specific entities within the text.

Yu et al. [7], Deep Learning models, specifically BERT-BiGRU, demonstrated superior performance in social media data classification, achieving an accuracy of up to 95%. Similarly, in the context of Thailand, research by Wanassawan and Ekarat [8] evaluated models for classifying consumer review topics on e-commerce platforms. Their findings indicated that Random Forest and WangchanBERTa models could effectively categorize key issues—such as logistics, promotions, and system performance—and perform sentiment analysis with high precision, ranging from 75% to 85%.

2.2 The 7P's Service Marketing Mix for E-commerce

The 7P's Marketing Mix theory, proposed by Booms and Bitner (1981) [10], builds upon the traditional 4P model (Product, Price, Place, and Promotion) originally developed by McCarthy (1964). Booms and Bitner extended this framework to include three additional elements: People, Process, and Physical Evidence, with the objective of enhancing competitive marketing tools. In the context of E-commerce, the components of the 7P's model are defined as follows.

1) **Product:** Encompasses the manufacturing and goods, distribution channels, and the provision of product and service information through internet-based trading channels or online storefronts.

2) **Price:** Strategies must maintain flexibility to adapt to dynamic market conditions.

3) **Place:** In E-commerce, "Place" refers to digital presence, including websites, online shopping platforms, social media commerce, and mobile applications.

4) **Promotion:** Involves integrated system tools that display purchase results and payment gateways, alongside social media advertising to enhance brand accessibility for consumers.

5) **Process:** Covers the entire workflow from product sourcing to commercial logistics, including automated business-driven information services.

6) **People:** Reflects the human interaction and movement throughout the business cycle, ranging from the initial point of contact to back-end business processes.

7) **Physical Evidence:** Refers to the "virtual environment," such as a functional e-commerce website, social media marketplaces, or mobile apps, including the responsiveness and interaction provided to consumers during their journey.

2.3 The Marketing Mix (7P's)

The Marketing Mix is a critical strategic tool used to address consumer needs and enhance overall satisfaction [11]. This is particularly evident in service industries and for complex products such as gems and jewelry. Applying the 7P's framework—which extends to include People, Process, and Physical Evidence—is essential for establishing a sustainable competitive advantage.

A review of literature regarding online jewelry purchasing decisions reveals that the components of the marketing mix influence consumers to varying degrees. Kanokwan [13] investigated online consumer behavior, technology acceptance, and the marketing mix affecting jewelry purchase decisions. The study indicated that the marketing mix was the most significant factor, outweighing technology acceptance and online behavioral factors.

In contrast, Ubon [14] focused on factors influencing jewelry purchases via social commerce in Thailand. The findings specifically highlighted that Product, Service (People/Process), and Place were the primary variables significantly impacting purchasing decisions. Conversely, Price and Promotion were found to have a relatively lower impact in certain contexts. Furthermore, Kanathat [15] explored the intersection of the marketing mix, technology acceptance, and online consumer behavior, discovering that in some instances, behavior and technology acceptance might exert a more direct influence than the marketing mix itself.

Given these diverging empirical results, the researcher aims to utilize these findings as a foundation for analyzing authentic user reviews. This study seeks to identify which of the 7P's factors are most prioritized by customers and contribute most significantly to their satisfaction within the e-commerce context, as expressed through their textual reviews.

3 Data and Methodology

3.1 Data

1) Data Collection

The researcher collected consumer reviews for gemstone bracelets from three leading and highly popular retailers: Ravipa, Harmanstone, and Jewel Land, across the Shopee and Lazada e-commerce platforms. Data was retrieved using a Web Scraper tool, covering historical reviews from 2022 to 2023. The initial data collection yielded a total of 5,958 entries.

2) Data Preprocessing

Following the removal of duplicate and irrelevant entries, a final dataset of 5,766 reviews remained for analysis. The researcher performed data preparation using Natural Language Processing (NLP) techniques, categorized into the following stages:

- Data Labeling: Each review was manually categorized based on the 7P’s Marketing Mix framework and assigned a Sentiment score (Positive, Neutral, or Negative).
- Data Cleansing: This involved removing special characters, punctuation marks, and emojis that did not contribute to the contextual analysis.
- Text Normalization: Misspelled words were corrected, and word forms were standardized according to the dictionary using the PyThaiNLP library.
- Word Tokenization: The newmm engine from the PyThaiNLP library was utilized for segmenting text into individual tokens (word units), facilitating the subsequent vectorization process.

3.2 Methodology

The researcher followed the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework for data analysis, with the technical details outlined as follows:

1) Feature Extraction

The TF-IDF (Term Frequency-Inverse Document Frequency) technique was employed to transform textual data into numerical vectors. The ngram_range was set to (1, 2) to capture both individual words and bigrams, preserving the contextual relationships between word pairs. Additionally, the max_features was limited to 3,500 to retain significant attributes while reducing data dimensionality and filtering out non-essential information.

2) Handling Imbalanced Data

The dataset was partitioned into a Training Set (80%) and a Test Set (20%). Given the high disparity in review volume across different factors, the researcher applied the Proportional SMOTE (Synthetic Minority Over-sampling Technique) exclusively to the training set. A growth rate of 4x was established, with a constraint that the synthetic samples would not exceed the size of the majority class. This approach was chosen to maintain the original data ranking and priority while preventing the risk of overfitting.

Table 1. Comparison of Training Set Distribution Before and After Data Balancing (SMOTE)

Marketing Mix Factors	Original Count (Pre-SMOTE)	Balanced Count (Post-SMOTE)
Product	1,539	1,539
Process	1,116	1,539
People	652	1,539
Price	402	1,539
Promotion	385	1,539
Place	244	976
Physical Evidence	274	1,096

As illustrated in Table 4, the initial training set exhibited a significant data imbalance across the various factors. To address this, the researcher employed the SMOTE (Synthetic Minority Over-sampling Technique) to generate synthetic data for the minority classes. The process was configured with a 4x growth rate, with a strict constraint that the total count must not exceed the volume of the majority class.

The results of this balancing process indicate that factors previously limited by sparse data—such as Place and Price—now possess a sufficient volume for the model to learn their distinct characteristics more effectively. Furthermore, this approach preserves the natural hierarchical ranking of the factors found in the original dataset, ensuring the realism of the model's performance evaluation.

3) Modeling and Evaluation

The researcher compared the performance of six classification models, comprising Logistic Regression, Random Forest, Multinomial Naïve Bayes, Support Vector Machine (SVM), XGBoost, and the Thai large language model, WangchanBERTa.

For WangchanBERTa, the researcher performed Fine-tuning with the following hyperparameters

Table 2. Fine-tuning with the hyperparameters

Parameters	Value
Learning Rate	$1 \times 10^{\wedge -5}$
Batch Size	15
Epochs	20

All models were evaluated using standard performance metrics, including Accuracy, F1-score, and the Area Under the ROC Curve (ROC AUC) to determine the models' ability to distinguish between different factors effectively.

Table 3. WangchanBERTa Model Training and Evaluation Results per Epoch

Epoch	Training Loss	Validation Loss	Accuracy	F1-score	ROC AUC (Weighted)	ROC AUC (Macro)
1	-	3.3569	0.3484	0.2644	0.6525	0.6578
2	-	3.1829	0.4419	0.3639	0.7065	0.7013
3	-	2.7312	0.5173	0.4616	0.7966	0.7968
4	3.1624	2.2504	0.6352	0.6131	0.852	0.8574
5	3.1624	2.1067	0.6525	0.6416	0.8611	0.8688
6	3.1624	1.9824	0.6811	0.6722	0.8781	0.8832
7	2.0507	1.7579	0.7088	0.7042	0.8999	0.9116
8	2.0507	1.7098	0.7184	0.7187	0.9081	0.9164
9	2.0507	1.6850	0.7184	0.7137	0.9091	0.9203
10	2.0507	1.6401	0.7314	0.7287	0.9159	0.9265
11	1.4116	1.6183	0.7366	0.7327	0.9177	0.9289
12	1.4116	1.6428	0.7340	0.7303	0.9182	0.9287
13	1.4116	1.6249	0.7348	0.7335	0.9198	0.9303
14	1.0586	1.6539	0.7348	0.7335	0.9198	0.9303

15	1.0586	1.6798	0.7392	0.7365	0.9193	0.9294
16	1.0586	1.6787	0.7357	0.7335	0.92	0.9307
17	1.0586	1.6866	0.7409	0.7387	0.9198	0.9311
18	0.8478	1.6838	0.7400	0.7378	0.9204	0.9315
19	0.8478	1.695	0.7383	0.7363	0.9199	0.9309
20	0.8478	1.6987	0.7374	0.7374	0.9194	0.9308

As shown in Table 3, the WangchanBERTa model exhibited rapid learning during the initial stages, with performance beginning to converge from Epoch 7 onwards. The researcher selected the model from Epoch 11 as the optimal iteration for final inference. This specific epoch was chosen because it reached the lowest Validation Loss (1.6183) before showing an upward trend in subsequent rounds. This selection represents the most effective balance between model learning and generalization, ensuring high performance on unseen data.

Table 4. WangchanBERTa Model Training and Evaluation Results per Epoch

Model Name	Technique	Accuracy	F1-score	ROC AUC	Weighted Average AUC
Logistic Regression	TF-IDF + SMOTE	0.7175	0.7186	0.9276	0.9082
RandomForestClassifier	TF-IDF + SMOTE	0.7392	0.7380	0.9373	0.9212
MultinomialNB	TF-IDF + SMOTE	0.6655	0.6612	0.9142	0.8963
SVM	TF-IDF + SMOTE	0.7261	0.7263	0.9321	0.9142
XGBClassifier	TF-IDF + SMOTE	0.7539	0.7530	0.9362	0.9196
WangchanBERTa	Fine-tuning	0.7409	0.7387	0.9310	0.9198

Based on the results in Table 4, XGBClassifier achieved the highest classification accuracy for online jewelry purchasing factors at 75.39%, with an F1-score of 75.30% and an ROC AUC of 93.62%. For WangchanBERTa, after fine-tuning (Learning Rate: 1 x $10^{\wedge -5}$, Batch Size: 15, 20 Epochs), the peak accuracy of 74.09% occurred at Epoch 17. However, Epoch 11 was selected as the optimal deployment point due to its minimum Validation Loss (1.6183), serving as an effective "Early Stopping" point to ensure better generalization.The slight performance lead of XGBoost over WangchanBERTa (Deep Learning) can be attributed to the nature of jewelry reviews, which are often short and limited in volume. In such cases, statistical models focusing on term weights can capture patterns more effectively, while offering faster processing and clearer interpretability for marketing strategies.Furthermore, despite applying SMOTE to handle data imbalance, the F1-score and ROC AUC were prioritized to verify class discriminability. Notably, Random Forest yielded the highest ROC AUC (93.73%), marginally surpassing XGBoost (93.62%). This suggests that while XGBoost excels in overall prediction accuracy, Random Forest's bagging algorithm is superior at ranking probabilities and distinguishing between the 7P's factors. Its robustness against synthetic data noise from SMOTE allows for clearer decision boundaries between classes.

4) Word Co-occurrence Network Analysis

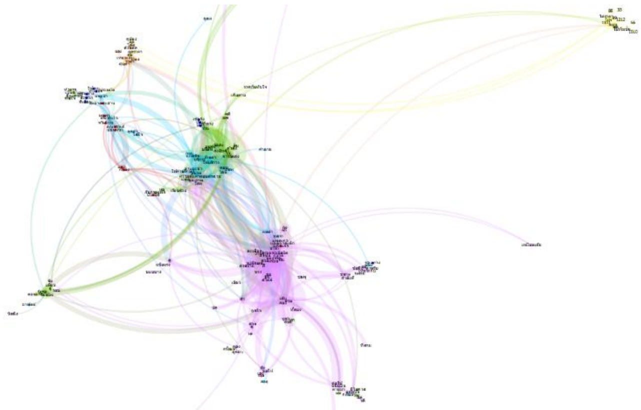

Fig.2 illustrates the co-occurrence network of marketing factors.

The node size represents Degree Centrality, indicating the relative importance or connectivity of a keyword, while the edge thickness reflects the Weight (frequency of co-occurrence). The identified clusters align with the 7P's Marketing Mix as follows:

- Product (Pink Cluster): Keywords such as "beautiful," "color," "cute," "design," and "bracelet" form a dense group. This suggests that aesthetic appeal—specifically color, delicate size, and cuteness—is the primary focus. Additionally, the term "Mutelu" (spiritual belief) shows a significant connection, reflecting the cultural value of the products.
- Process (Green Cluster): This largest cluster features strong links between "fast delivery," "store shipping," and "logistics." It confirms that packaging efficiency and delivery speed are the most frequently discussed and prioritized issues among consumers.
- People (Light Blue Cluster): High connectivity between "admin," "responsive," "service," and "advice" indicates that consumers value promptness and the quality of consultation. Terms like "excellent response" highlight the importance of politeness and helpfulness.

- Price (Orange Cluster): Words such as "worth," "expensive," "reasonable," and "economical" are closely linked, showing that consumers evaluate price primarily based on perceived value for money.
- Promotion (Yellow Cluster): Strong associations between "discount," "promotion," "coupon," and "limited time" indicate that purchase decisions are significantly driven by time-sensitive incentives and promotional campaigns.
- Place (Dark Blue Cluster): While less dense, terms like "accessible," "website," "convenient," and "repeat purchase" suggest that platform usability and store reliability directly influence long-term customer loyalty and repeat business.
- Physical Evidence (Red Cluster): Centered around "unboxing," this cluster connects to "premium quality" and "secure packaging." This represents the brand's "signature" physical touchpoints that consumers remember most vividly.

4 Policy Recommendation

4.1 Process and Supply Chain Management Strategy

The study indicates that "Aesthetic Appeal" (Product) and "Delivery Speed" (Process) are critical factors with the highest correlation in consumer reviews. Therefore, entrepreneurs should implement the following:

1) Aesthetic-Driven Product Design

Focus on "minimal," "cute," and "elegant" designs. It is imperative that the physical product strictly matches the marketing imagery to ensure perceived quality.

2) Logistics Optimization

Maintain "Ready-to-ship" inventory levels and minimize Lead Time in order fulfillment to meet consumer expectations for speed.

3) Responsive Communication

Administrators must prioritize rapid response times for order status updates and initial inquiries to minimize customer waiting periods. Furthermore, maintaining a polite and professional tone in all interactions is essential. This combination of speed and courtesy significantly enhances service satisfaction, fostering customer loyalty and increasing the likelihood of repeat purchases.

4.2 Digital Marketing Communication Strategy

Feature extraction revealed specific consumer preferences and niche demands. These insights should be utilized for content planning:

1) SEO and Product Naming

Incorporate high-frequency keywords found in reviews—such as "minimal," "elegant design," or "cute bracelet"—into product titles and descriptions to improve search visibility on e-commerce platforms.

2) Targeted Value Propositions

Emphasize product strengths that align with customer expectations, particularly visual consistency (e.g., "What You See Is What You Get"), to build pre-purchase confidence.

4.3 Physical Evidence and Trust-Building Strategy

As jewelry carries high emotional and monetary value, Physical Evidence is vital for establishing trust:

1) Unboxing Experience

Prioritize premium packaging design and secure wrapping. As the only tangible touchpoint in the online journey, a high-quality "unboxing" experience significantly boosts brand image and encourages positive word-of-mouth (e-WOM).

4.4 Technological Development and Data Asset Policy

To foster sustainability in the online jewelry industry, government agencies and relevant organizations should support the following policies:

1) Specialized Custom Dictionary Development

Support the creation of a specialized Thai jewelry and e-marketing lexicon. This will overcome current NLP limitations, improve contextual accuracy, and enable entrepreneurs to access real-time consumer insights efficiently.

2) Cross-platform Data Integration

Promote the collection and analysis of data across multiple platforms (e.g., TikTok Shop and other social commerce channels). This "Cross-platform" approach will mitigate data bias and provide a more comprehensive and accurate overview of the jewelry market landscape.

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