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Enhancing Tablet Product Experience on AliExpress: A Data-Driven Analysis of Online Customer Reviews

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Abstract: In the competitive e-commerce landscape, understanding customer experience is critical for businesses to enhance satisfaction and drive sales, particularly for tablet products. This study provides in-depth insights into customer experiences with tablet products on the AliExpress platform by analyzing 4,469 online reviews through sentiment analysis and topic modeling. The sentiment analysis reveals that while a significant portion of reviews are neutral to slightly negative, the overall sentiment is positive, indicating general satisfaction. Topic modeling uncovers key themes, with positive discussions centered around fast delivery, value for money, and children's enjoyment, while negative themes highlight issues with screen performance, customs processes, and unexpected taxes, particularly for Brazilian customers. Temporal analysis shows dynamic spikes in topics like fast delivery and cost-benefit during specific periods. These findings provide actionable guidance for businesses and manufacturers to optimize tablet quality, logistics, and marketing strategies to meet the needs and preferences of their target audience better.

Keywords: Customer experience, tablet products, online reviews, sentiment analysis, topic modelling, e-commerce.

Introduction

In the digital age, e-commerce platforms like AliExpress have revolutionized shopping experience, offering consumers convenience, variety, and competitive prices. This evolution has provided consumers with easy access to information, multiple purchasing channels, and the ability to compare brands effortlessly [1]. However, the rise of these platforms has also introduced challenges, such as algorithmic price discrimination, which can negatively impact consumer loyalty and perceived platform ethics, particularly for price-sensitive customers with initial trust [2]. This duality underscores the complex dynamics of consumer behavior in the digital marketplace and highlights the importance of understanding customer experiences on these platforms.

AliExpress, one of the largest global e-commerce platforms, presents a unique case study due to its vast international reach and diverse product offerings, including a significant tablet market. The platform's prominence in cross-border e-commerce makes it an ideal subject for examining customer experiences in a global context. Customer feedback on AliExpress, particularly for products like tablets, is crucial for optimizing the product experience and informing business strategies [3]. Online consumer reviews and ratings significantly influence purchasing decisions, emphasizing their importance in shaping consumer choices [4]. Numerous studies have highlighted the impact of these reviews on consumer decision-making processes and purchase behavior [5]; [6]; [7].

To obtain valuable insights from the vast amount of unstructured data in online customer reviews, various text mining and sentiment analysis techniques have been employed. Sentiment analysis tools like Naïve Bayes are utilized to understand and analyze customer feedback, providing valuable insights into how customers perceive products and services [8]. Various methods, such as collaborative filtering algorithms, are employed to gather feedback and enhance the user experience on e-commerce platforms like AliExpress [9]. [10] proposed a fusion sentiment analysis method that combines textual analysis techniques with machine learning algorithms to mine online product experiences and track customer demands. This approach enables businesses to identify sentiment polarities and extract sentiment topics, providing a comprehensive understanding of customer feedback. [11] analyzed the multidimensionality of information embedded in online product reviews, including sensory, cognitive, affective, and social dimensions, demonstrating the rich diagnostic value of these reviews for prospective customers.

In the broader e-commerce domain, several studies have focused on understanding and improving the online customer experience (OCE) through the analysis of customer reviews. [12] explored the use of sentiment analysis on social media data to enhance customer experience and inform marketing strategies. [13] proposed interpretable neural networks for analyzing customer reviews, enabling the estimation of nonlinear relationships and visualizing the results to better comprehend customer experiences. [14] and [15] provided comprehensive reviews of the antecedents and consequences of OCE in the purchase context, shedding light on factors that shape consumers' online shopping behavior and their implications for online retailers.

Researchers have also examined various dimensions of customer experience and their applications in market segmentation. [16] conducted a systematic review of literature on customer experience, identifying its dimensions, antecedents, and consequences. In a more recent study, [17] explored customer experience in the context of social commerce, developing a conceptual framework to understand its experiences and consequences in this specific setting. Another study by [18] investigated market segmentation based on customer experience dimensions extracted from online reviews using data mining techniques, underscoring the potential for personalized marketing strategies.

While numerous studies have analyzed online reviews across various product categories, specific research on understanding customer experience with tablet products through online reviews is relatively limited. [19] examined the impact of tablet computer attributes on consumer purchase intention, highlighting the importance of factors such as perceived usefulness and ease of use. [20] investigated the adoption of tablet devices in educational settings, emphasizing the need to understand user experiences in specific contexts. However, these studies did not utilize online reviews as their primary data source, leaving a gap in understanding real-world customer experiences.

Schlebbe explored the uses and gratifications of tablet computers for children by analyzing online customer reviews for Amazon's Fire Tablet Kids Edition [21]. The research provided insights into the specific market segment. [22] proposed a data mining approach to analyze online reviews of tablet products, aiming to support product customization based on customer opinions. However, their study did not examine the overall customer experience with tablet products, particularly in the context of a global e-commerce platform like AliExpress.

Based on the reviewed literature, there is a notable gap in understanding customer experiences with tablet products on e-commerce platforms such as AliExpress through the lens of online reviews. This study aims to fill this gap by providing valuable insights into customer perceptions, satisfaction levels, and areas for improvement in the tablet product category on this platform. This study can inform businesses operating in the online retail sector and contribute to the body of knowledge on customer experience analysis in this field by utilizing the "voice of the customer" through online reviews. Moreover, this study aligns with the emerging trend of utilizing data-driven approaches and harnessing the wealth of information available in online customer reviews. The implications for businesses are substantial, providing strategies for product and service enhancement based on customer feedback, achieved by integrating advanced analytical techniques with the rich data from AliExpress customers.

Methods

This study began with the collection of 4,469 online reviews from AliExpress, focusing on tablet products from four brands: Pritom, Lenovo, Alldocube iPlay, and Teclast. The data were preprocessed, which included the removal of non-English reviews, text cleaning (removal of special characters and punctuation, and conversion to lowercase), tokenization, stopword removal, and lemmatization to reduce words to their base form. This prepared the data for subsequent analysis, starting with aspect identification to highlight key tablet features discussed in the reviews.

Sentiment analysis was conducted using the VADER tool from NLTK to determine the overall sentiment expressed in the reviews. Concurrently, topic modeling was performed using the BerTopic algorithm to uncover latent themes within the text. This process involved clustering reviews into thematic groups based on their content. The insights gained from both sentiment analysis and topic modeling were then analyzed, providing a deeper understanding of customer feedback. The insights led to conclusions and actionable recommendations for improving the tablet product experience.

Data Collection

In this study, we collected 4469 reviews from AliExpress, a popular e-commerce website. These reviews were about the best-selling tablets from four different brands with different models: Pritom, Lenovo, Alldocube iPlay, and Teclast. To ensure that the data was accurate, we carefully removed any duplicate reviews and ones missing important information. Additionally, we streamlined the dataset by eliminating unnecessary columns. The final dataset contains 3,828 reviews, each with at least five words, customer ratings from 1 to 5 stars, the date the review was written, the name of the reviewer, and the product's name. This cleaned dataset is a valuable resource for studying consumer opinions and product evaluations.

Data Preprocessing

In this study, we conducted a comprehensive preprocessing of the collected online customer reviews following these steps: Non-English reviews were removed from the dataset. Text Cleaning: The text data were cleaned by removing any irrelevant or noisy information. This involves tasks such as removing special characters, punctuation, and non-alphanumeric symbols. Additionally, we converted the text to lowercase to ensure consistency in the analysis. Tokenization: The tokenization involved breaking down the text into individual words. This step is essential for further analysis, as it allows for the extraction of meaningful information from the text data. Stopword Removal: Common stopwords (e.g., “and,” “the,” “is”) were removed from the text data. Stopwords are frequently occurring words that typically do not carry significant meaning in the context of sentiment analysis and attribute extraction. Lemmatization or Stemming: Lemmatization and stemming were applied to reduce words to their base or root form. This step helps in standardizing the text data and reducing the complexity of the vocabulary, which can improve the accuracy of subsequent analysis.

Sentiment Analysis

Sentiment analysis was performed on the cleaned review text to understand the overall sentiment expressed in the reviews. The VADER (Valence Aware Dictionary and sentiment Reasoner) sentiment analysis tool from NLTK was employed. VADER, a straightforward rule-based model, is commonly used for general sentiment analysis [23]. The sentiment scores were then aggregated and normalized by the total number of reviews for each brand to enable fair comparisons across brands.

Aspect Identification

To identify the most frequently discussed aspects related to tablet features, a list of predefined keywords was created by extracting frequently mentioned features of tablets in the tokenized review text, including "screen," "battery," "performance," "cost," "camera," and "design."

Topic Modeling

The topic modelling methodology employed in this study is based on the BERTopic algorithm [24], which leverages pre-trained language models and unsupervised machine learning techniques to extract latent topics from text data [25]. The methodology can be summarized as follows:

Embedding: The review text is converted into high-dimensional vector representations using a pre-trained sentence transformer model (BAAI/bge-m3). This step captures the semantic meaning of the text in a numerical format suitable for downstream analysis.

Dimensionality Reduction: The high-dimensional embeddings are reduced to a lower-dimensional space using the UMAP (Uniform Manifold Approximation and Projection) algorithm. This step facilitates the visualization and clustering of the embeddings while preserving the essential information.

Clustering: The reduced embeddings are clustered using the HDBSCAN (Hierarchical Density-Based Spatial Clustering of Applications with Noise) algorithm. This step groups together similar embeddings, representing potential topics within the review text. The minimum cluster size is set to 20, which determines the granularity of the identified topics.

Vectorization: The review text is converted into a numeric matrix format using the CountVectorizer from scikit-learn. This step prepares the text data for topic representation and interpretation.

Topic Representation: The KeyBERT Inspired model is employed to extract representative keywords and phrases for each identified topic. These keywords and phrases help interpret and label the topics.

Model Training: The BERTopic model is trained using the embedding model, dimensionality reduction model, clustering model, vectorizer model, and representation model specified in the previous steps. The model ingests the review text and the corresponding embeddings to identify the latent topics.

Topic Assignment: Each review is assigned to the most probable topic identified by the BERTopic model, and the corresponding topic probabilities are calculated. This information is stored in the dataset for further analysis.

Topic Visualization and Interpretation: The trained BERTopic model provides various functionalities for visualizing and interpreting the identified topics. These include retrieving representative keywords and review excerpts for each topic, visualizing the topic distributions, analyzing topic relationships, and exploring topic hierarchies.

The BERTopic algorithm combines advanced natural language processing techniques, such as pre-trained language models and unsupervised learning algorithms, to extract meaningful topics from the review text. The identified topics can provide valuable insights into consumer preferences, concerns, and areas for product improvement, ultimately informing strategic decision-making processes.

Results and Discussions

Sentiment Analysis

The sentiment analysis performed on the cleaned review text revealed nuanced insights into consumer perceptions and attitudes toward different tablet brands. The distribution of sentiment scores, as shown in Figure 1 reveals that the most prominent feature is a large peak in the bin between -0.10 and 0.00, spanning both slightly negative and neutral sentiments, which necessitates careful interpretation.

To accurately interpret the sentiment distribution, we considered the standard thresholds for the VADER sentiment analysis tool. Compound values between -0.05 and +0.05 represent neutral sentiment, values below -0.05 indicate negative sentiment, and values above +0.05 indicate positive sentiment. Based on these thresholds, several key observations emerge:

A significant portion of reviews falls in the neutral to slightly negative range, as evidenced by the highest bar in the histogram.

The sentiment distribution exhibits a notable positive skew, with a substantial number of reviews having compound scores between 0.40 and 0.90.

Positive sentiment is not evenly distributed but shows increasing frequency as the sentiment score approaches 1.00, with the highest positive frequencies occurring between 0.70 and 0.90.

Strongly negative reviews are relatively rare, as indicated by the low bars on the far left of the histogram.

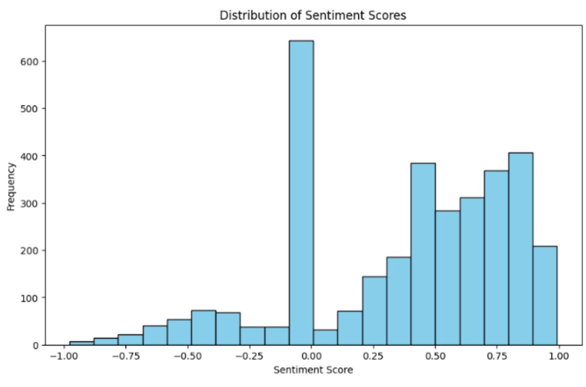

Figure 1. Distribution of sentiment scores

This distribution suggests that while there is a large cluster of neutral to slightly negative reviews, the overall trend leans towards positive sentiment, with a significant number of highly positive reviews. The presence of a substantial neutral segment indicates that many customers may have mixed or moderate feelings about their tablet experiences on AliExpress. The predominance of positive sentiments suggests overall satisfaction, while the significant neutral segment indicates opportunities for enhancing the customer experience to shift these neutral opinions towards the positive end of the spectrum.

Aspect Identification

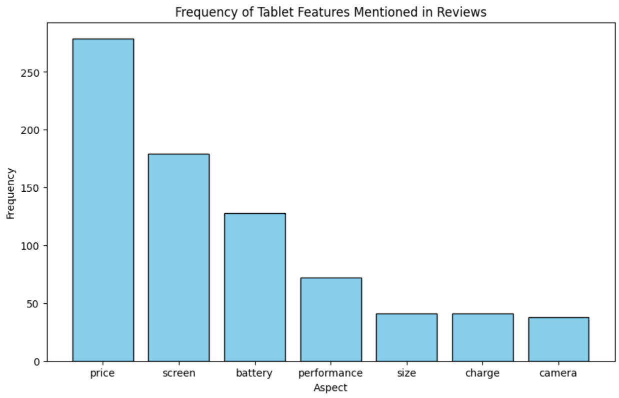

Figure 2. Frequency of mentioned tablet features

The analysis of frequently mentioned aspects related to tablet features provides valuable information for product improvement strategies. As depicted in Figure 2, the most commonly discussed aspects were "price," "screen," and "battery," indicating that consumers place a high emphasis on these aspects when evaluating tablet products.

Interestingly, the aspect "camera" received relatively fewer mentions, suggesting that it may be a lower priority for consumers in the tablet market compared to other features. This insight could inform product development and marketing strategies, allowing manufacturers to focus their efforts on the aspects that matter most to consumers.

Topic Modeling

The BERTopic model was employed to uncover the latent topics present in the review text, providing valuable insights into the key themes and concerns expressed by consumers. The model identified several distinct topics, each represented by a set of descriptive keywords and associated with a subset of reviews. Table 1 presents a summary of the most prominent topics identified by the BERTopic model, along with their representative keywords and representative review excerpts. The distribution of topics across different brands, as visualized in the intertopic distance map (Figure 3), reveals distinct patterns. Here are some explanations about the intertopic distance map:

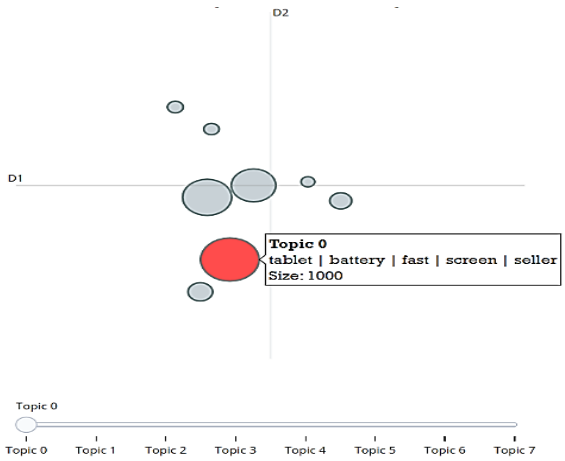

Figure 3. Intertopic distance map

Topic clusters: There appear to be two main clusters of topics. One cluster includes topics 0, 1, 2, and possibly 5 and 6 (Table 1). These topics seem to be positive and focus on general product satisfaction (e.g., battery life, screen quality, fast delivery, cost-benefit, children enjoying the tablet). The other cluster includes topics 3, 4, and 7. These topics are more negative and mention issues such as slow performance, screen problems, customs refunds (particularly for Brazil), and unexpected taxes.

Outliers: Topic 7 (Taxed_Customs_Tax_Real Number) appears to be an outlier, located far away from all other topics. This suggests that this topic is unique and not closely related to any other topic in the dataset.

Table 1. Summary of prominent topics identified by BERTopic

Topic	Name	KeyBERT keywords	Representative documents	Analysis
0	Tablet_Battery_Fast_Screen	tablet, battery, fast, screen	tablet, tablets, device	This is a broad topic likely capturing general positive sentiment about the core functionalities of a tablet (battery life, screen quality, etc.).
1	Fast_Delivery_Packed Shipping	fast, delivery, packed, shipping	delivery fast, fast delivery	This topic focuses on positive experiences with the delivery process, highlighting speed and secure packaging.
2	Liked_Cost_Thank (Cost-Benefit)	liked, cost, thank, cost benefit	price excellent, great cost benefit	This topic captures reviews that emphasize value for money and positive price-to-performance ratio.
3	Slow_Screen_Bad (Little Slow)	slow, screen, bad, little slow	slow, little slow	This topic focuses on negative experiences with performance, particularly slowness and screen quality issues.
4	Refund_Customs_Returned (Brazil)	refund, customs, returned, brazil	refund, received product	This topic likely reflects issues specific to Brazilian customers, mentioning refunds, customs problems, and product returns.
5	Daughter_Loved	daughter, daughter loved, loved, my daughter	daughter loved, my daughter loved	This topic highlights positive experiences with children using the tablet.
6	Children_Son_Kids_Loves	children, son, kids, loves	my son loved, beautiful children	Similar to topic 6, this focuses on positive experiences with children enjoying the tablet.
7	Taxed_Customs_Tax_Real Number	taxed, customs, tax, real number	taxed real number	This topic likely reflects concerns about customs taxes, particularly for buyers who might pay an unexpected "real number" tax.

The similarity matrix (Figure 4) provides insights into the relationships between topics. The BERTopic algorithm was used to calculate these similarities, which leverages pre-trained language models and unsupervised machine learning techniques to extract and visualize latent topics from text data. We can see that several topics have complex relationships. The analysis reveals that categories such as "Fast Delivery Packed Shipping" and "Liked Cost Thank (Cost-Benefit)" show a high similarity score, indicating that comments about fast delivery and proper packaging are often associated with positive feedback on cost and overall satisfaction. Similarly, "Daughter_Loved" and "Children_Son_Kids" also exhibit high similarity, demonstrating that positive comments about daughters frequently correlate with positive comments about children and sons. Conversely, pairs like "Children_Son_Kids" and "Refund Customs Returned (Brazil)" as well as "Daughter_Loved" and "Refund_Customs_Returned_(Brazil)" show very low similarity, suggesting that issues related to children and sons are rarely mentioned in the context of refund and customs issues in Brazil.

This matrix highlights how positive experiences with fast delivery and child-related enjoyment are interconnected, while issues like customs and refunds stand apart from these positive themes.

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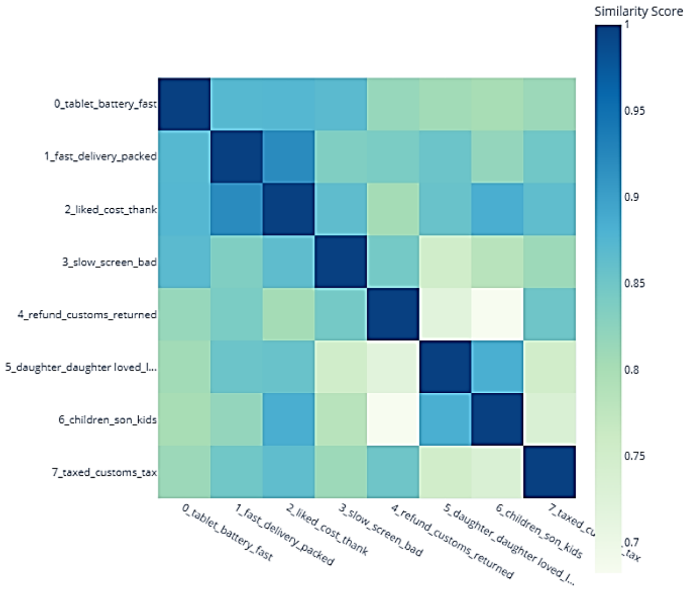

Figure 4. Similarity matrix

The analysis of topics per product class (Figure 5) reveals dominant topics associated with different product categories or models. Topic 0 (tablet_ battery_fast_screen) emerges as the most frequent topic for all models except the "lenovo_legion_y700," which is primarily dominated by Topic 1 (fast_delivery_packed_ shipping). This indicates that for most tablet models, user discussions are heavily centered around battery life and screen performance, underscoring these features as primary concerns. In contrast, for the "lenovo_legion_y700," fast delivery and efficient packaging are the leading topics of interest. This pattern highlights the consistent emphasis on battery and screen quality across most devices, while shipping efficiency takes precedence for the "lenovo_legion_y700."

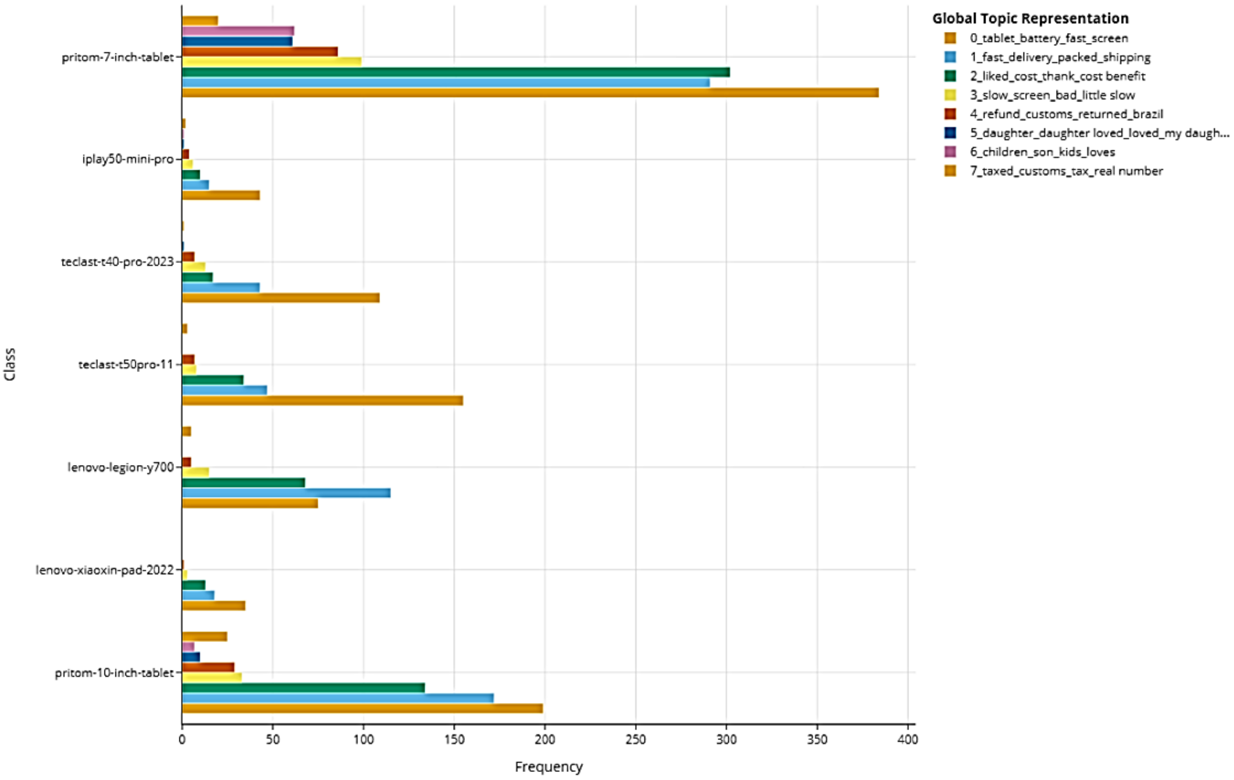

Figure 5. Topic per class

Figure 6 shows the frequency of different topics mentioned in tablet reviews on AliExpress over a six-month period, from May 2023 to October 2023. Here are some observations based on the graph:

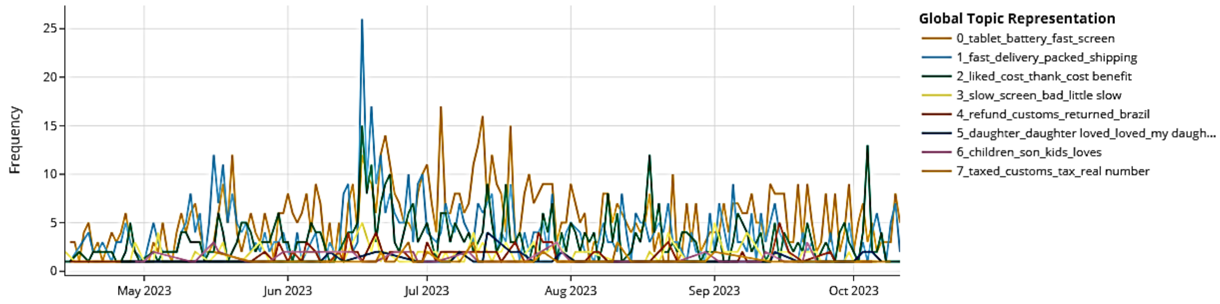

Figure 6. Topics over time

Consistency Over Time: Topics 3 (slow_screen_bad_little_slow), 4 (refund_customs_returned_brazil), 5 (daughter_daughter loved_loved_my daughter), 6 (children_son_kids_loves), and 7 (taxed_customs_tax_real number) maintain a relatively constant level of discussion from May 2023 to October 2023. These topics show minimal fluctuations and do not exhibit significant peaks, indicating stable, ongoing engagement.

Mid-June Increase: Starting in mid-June, there is a noticeable increase in frequency for Topic 1 (fast_delivery_packed_shipping), which reaches the highest peak observed in the graph. This suggests a sudden surge in discussions related to delivery speed and packaging during this period.

Topic 2 Peaks: Several peaks for Topic 2 (liked_cost_thank_cost benefit) occur through, June, August, and October, indicating intermittent but notable user interest in cost-related feedback during these months.

Topic 0 Fluctuations: Topic 0 (tablet_battery_fast_screen) shows several peaks through June and July. Despite these peaks, the frequency remains lower than the mid-year peak of Topic 1, indicating that while battery life and screen performance are significant concerns, they do not surpass the urgency of delivery issues in mid-June.

Event-Driven Spikes: The temporal pattern reveals that topics related to customs, refunds, and family references remain steady, while discussions about delivery and cost fluctuate more, likely driven by specific events or changes in user experiences.

Monitoring Dynamics: This analysis highlights the importance of closely monitoring dynamic topics such as delivery and cost issues to quickly address user concerns, while also maintaining consistent attention to stable topics like tax and customs to ensure ongoing user satisfaction.

Finally, the hierarchical clustering dendrogram in Figure 7 depicts the thematic relationships between various customer reviews.

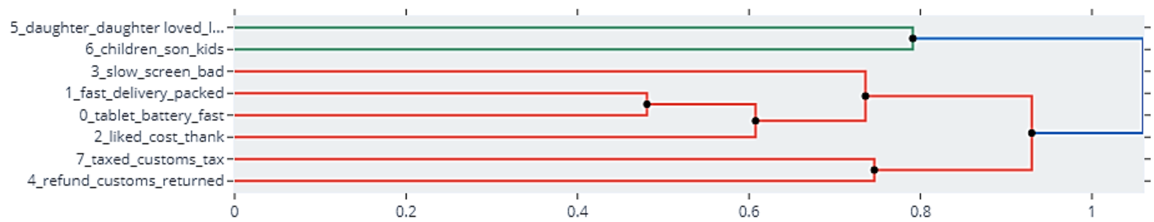

Figure 7. Hierarchical clustering

The reviews can be broadly categorized into the following key groups:

Strongest Association**:** The closest link is observed between topic 1 ("fast_delivery_packed") and topic 0 ("tablet_battery_fast"), as these two topics are joined at the lowest point in the dendrogram. This indicates that customers who praised the fast delivery of the product often also mentioned its strong battery performance, showing a strong connection between these two aspects in their reviews.

Next Closest Connection: Topic 2 ("liked_cost_thank") is closely related to the combined pair of topics 0 and 1. While "liked_cost_thank" is linked to both delivery speed and battery life, it is slightly less directly associated compared to the strong bond between topics 0 and 1.

Logistical and Refund Issues: The connection between topic 7 ("taxed_customs_tax") and topic 4 ("refund_customs_returned") highlights recurring challenges in the post-purchase process. Customers who encountered taxation or customs issues were also likely to experience refund problems, indicating a pattern of dissatisfaction in this area.

Child-Related Satisfaction: Reviews focusing on topic 5 ("daughter_daughter_loved") and topic 6 ("children_son_kids") reflect customer satisfaction related to family use. These topics are closely linked, suggesting that customers who mentioned their children or family members were particularly pleased with the product.

This analysis of the dendrogram illustrates how various aspects of the product are interconnected in the minds of consumers.

The topic modeling analysis conducted using the BERTopic model has yielded rich insights into the key themes and concerns expressed by consumers in their reviews of tablet products. By leveraging these findings, manufacturers can gain a deeper understanding of consumer preferences, identify areas for improvement, and tailor their product development and marketing strategies to better meet the needs and expectations of their target audience.

Conclusions

The data-driven analysis of 4,469 online customer reviews for tablet products on AliExpress has provided valuable insights into the aspects of customer experience that drive satisfaction and dissatisfaction. Sentiment analysis revealed that while there is a significant portion of neutral to slightly negative reviews, the overall sentiment trends positively, indicating general customer satisfaction with tablet products. Aspect identification highlighted that features such as price, screen quality, and battery life are the most frequently discussed and valued by customers.

Topic modeling using the BERTopic algorithm uncovered distinct themes within the reviews. Key positive themes include fast delivery and secure packaging, value for money, and children's enjoyment of the tablets, while negative themes focus on slow performance, screen issues, and customs and tax problems, particularly for Brazilian customers. The analysis of topic frequencies over time showed that while some topics remained stable, others, such as delivery and cost-benefit, experienced significant peaks, reflecting their dynamic nature in customer discussions. The findings underscore the importance for businesses and manufacturers to focus on enhancing core tablet functionalities like battery life and screen quality, as well as improving logistics and addressing customs-related issues.

Despite the valuable insights, this research has some limitations. The analysis was confined to a specific time frame and may not capture long-term trends or seasonal variations in customer sentiment and preferences. Additionally, the sample was limited to reviews on the AliExpress platform, and expanding the research to include other major e-commerce channels could yield a more comprehensive understanding of the tablet market.

Future research could explore longitudinal analyses to identify evolving trends in customer experience, as well as cross-platform comparisons to gain a holistic view of the tablet market. Additionally, incorporating qualitative methods, such as in-depth interviews with customers, could provide deeper insights into the underlying motivations and pain points influencing their perceptions and purchase decisions.

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