Fanatics Sentiment Analysis: Understanding Brand Perception

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Introduction

In the ever-evolving landscape of e-commerce and social media, understanding customer sentiment towards a brand is paramount for informed decision-making and maintaining a positive reputation. Fanatics, a preeminent e-commerce platform specializing in sports merchandise and fan gear, serves as an interesting case study for understanding how its brand is perceived on various online platforms. Fanatics' remarkable dominance in the online marketplace can be primarily attributed to its agile supply chain processes, enabling it to swiftly deliver ready-to-buy merchandise. Whether it's the time-sensitive release of playoff merchandise for MLB or NFL teams, Fanatics has consistently met the demands of sports enthusiasts. However, our in-depth inquiry aims to uncover any potential trade-offs in this rapid process, encompassing factors like product quality and order fulfillment accuracy. Our project is designed to view this scenario from the customer's perspective – those who receive the merchandise. By conducting sentiment analysis, we aspire to gain valuable insights from the vast landscape of social media discussions. This comprehensive analysis will ultimately empower Fanatics to elevate customer engagement and satisfaction.

Data

Data Collection

Source 1: Trustpilot
Collecting Fanatics reviews on Trustpilot was relatively straightforward. The site's conventional URL changes for pagination made scraping easy. However, accurate review times posed a challenge due to users updating their reviews, causing HTML XPath changes. To address this, a pragmatic solution involved integrating a separate vector to capture updated data seamlessly, ensuring smooth dataset integration. This fix allowed the review post time to correctly match the appropriate corresponding posted reviews.

Source 2: Sitejabber
Sitejabber presented a more intricate challenge with its heavy reliance on JavaScript, deviating from conventional pagination. The next button at the bottom of the page triggers a JavaScript code that loads more data, making it difficult to collect. RSelenium was employed to fix this issue and navigate the pages on a remote driver. Fixing this problem was extremely hard; we needed to download Docker Desktop and run a container to simulate the remote driver. When the container started running on our desktops, we also needed to understand the right code to navigate the pages. The trickiest part was collecting the XPath variables inside the loop when the remote driver was up and running and then simulating the click on the next button to generate new reviews on the following pages. Unfortunately, our luck ran out as Sitejabber still did not allow our remote driver to simulate the pagination next click. We believe it had to do with different frames within the website. There may have been different frames that contained the

JavaScript and the variables we intended to scrape, and changing between them was very difficult to navigate. After exploring many debugging techniques, we resorted to our final method of scraping data from Sitejabber. We used Power Automate to scrape the data. Initially, scraping the data and appending it to an Excel file was challenging. It seemed as though it would only collect the data from the last page of reviews. Many methods were used to figure out what was wrong with appending each page to the Excel file. After careful consideration, a method of scraping fewer pages at a time was employed. This turned out to be successful as we were able to scrape 40 pages at a time, and the data was appropriately appended to the Excel file. One drawback we could not figure out, however, was collecting the attribute for the star rating of the reviews. Because the value was in an attribute, Power Automate struggled to collect the data, and when run separately, the integrity of the data was at stake, as matching the appropriate rating to the review was not guaranteed.

Source 3: Twitter

Our third and final data source came from Twitter, which may have been the trickiest to collect. After spending much time creating a Twitter development account, navigating the website, and figuring out the most appropriate queries to write in RStudio for a sound output of data, we learned that Elon Musk had rid the Twitter dev community of the education package for the Twitter API. A simple Google search would have sufficed and saved much time! Adapting to this news and deciding the best route to take was also somewhat tricky. After searching GitHub for Python and R code on how to scrape Twitter data, as well as consulting the source of all knowledge (YouTube) and evaluating different ways, we found one that most aligned with our goals. A kind YouTuber gave us a viable direction as well as his own website that laid out how to collect data using a browser. We went on Twitter and clicked inspect; from there, when we clicked on network, the feed from Twitter's backend was being intercepted from our browser and loaded into the network. The only drawback of this method is that we had to scroll down Twitter for this data to be intercepted, which meant we had to scroll for a while to gather the amount of tweets we wanted. After scrolling for a sufficient amount of time, there is a download button in the inspect section that downloads a HAR file. The HAR file can then be converted into a JSON file using the website that the kind YouTuber created. Due to the word "fanatics" meaning multiple things, unwanted tweets were apparent in the feed. To solve this issue, we searched for "fanatics jersey" and "fanatics apparel" and collected tweet results with those words in them. This created a limitation to the Twitter data, but we believe this is still a sufficient sample that contains the data we are analyzing.

Data Cleaning and Integration

After obtaining data from Sitejabber, cleaning involved refining the extracted information. Usernames, contents, and times were organized into a structured tabular format. The ratings column was processed to handle NA values. Whitespace was trimmed, and a new column identifying the data source "SiteJabber" was added, saving the cleaned data as "SiteJabber_reviews.csv".

Similar cleaning procedures were applied to Trustpilot data. Whitespace was removed from usernames, contents, times, and ratings; and a new column indicating the data source "Trust Pilot" was appended, resulting in "TrustPilot_reviews.csv".

Gathering and refining Twitter data involved distinctive challenges. To overcome the intricacies of handling JSON files, an external platform, JSON to CSV converter, was employed for efficient conversion. Subsequently, R code navigated complexities, extracting, and transforming Twitter data. Challenges arose due to nested structures within the JSON files, necessitating careful identification of correct column names. Despite these challenges, we were able to identify and extract the relevant variables within these large lists after loading the data into R. Similar cleaning techniques were applied to the "twitter" data frame, including renaming variables and changing data types and formats. The twitter data frame contained 3855 observations prior to cleaning, when null values contained within the content variable were dropped, the data frame decreased to 440 observations. The total observations decreased even more to 327 after extracting unnecessary tweets from the data frame, primarily advertisements. Feature engineering was deployed to create an engagement variable. We used the addition of likes and retweets for each specific tweet to signify the engagement with each tweet.

After meticulous extraction and cleaning of Sitejabber, Trustpilot, and Twitter data, a harmonization process streamlined information from diverse sources. Standardizing the data, each with unique complexities, required a multifaceted approach. Importing CSV, XLSX, and JSON files, the data was integrated into "all_source.csv" with 6 variables and 4327 observations. This consolidated dataset forms the foundation for nuanced insights into Fanatics' online presence and customer sentiment. The final version of "all_source.csv" used in data analysis contains the following fields in tabular format.

Data Dictionary

FIELD	TYPE	DESCRIPTION
USERNAME	Text	Username of the user that posted the content
CONTENT	Text	The textual content of the tweet/review
DATE	Date	Date the review/tweet was posted
RATING	Numeric	User rating for Fanatics products on website reviews
SOURCE	Text	The platform/source of the content
ENGAGEMENT	Numeric	Derived from the addition of retweets and likes for a tweet
SENTIMENT	Numeric	Net sentiment value derived from Bing lexicon

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Text Cleaning

In order to distill meaningful insights from the textual content of customer reviews, a systematic text cleaning process was meticulously implemented. The overarching objective was to prepare the raw text data for analysis by eliminating extraneous noise and irrelevant information. The following sequential steps were taken to achieve this:

Lowercasing
The initial step involved converting all text to lowercase. This essential transformation ensures uniformity in the text data, mitigating discrepancies in word counts and simplifying subsequent analyses.

Removing Punctuation
Punctuation marks were systematically removed to eliminate unnecessary symbols that do not contribute significantly to sentiment or content analysis. This step enhances the accuracy of sentiment analysis by focusing on the inherent meaning of the words.

Removing Numbers
Numeric characters were expunged from the text to streamline the analysis. This step ensures that the analysis focuses exclusively on the semantic content of the reviews, disregarding numerical data.

Removing Stop Words
Stop words, common words such as "is", "the", and "a", which frequently appear in the English language, were systematically excluded. These words, being non-informative, were removed to enhance the meaningfulness of the sentiment analysis.

Sentiment Analysis Implementation

Following the text cleaning process, sentiment analysis was conducted to quantitatively assess the emotional tone of each customer review. The Bing lexicon, a pre-built sentiment lexicon, was leveraged for this purpose.

Calculating Net Sentiment Score
A bespoke function, `calculate_net_sentiment`, was crafted to determine the sentiment score for each review. This involved counting the occurrences of positive and negative words in the review text and calculating the net sentiment score.

Applying the Sentiment Analysis Function
The sentiment analysis function was subsequently applied to the cleaned text data `Content_Cleaned` for each review in the dataset. This process resulted in a numerical sentiment score assigned to each review, providing a quantitative measure of the overall sentiment expressed in the text.

The careful cleaning of the text data and the following sentiment analysis are crucial steps in digging into how customers feel about Fanatics. This improved dataset is set to help us understand the Fanatics brand perception in more detail. Ultimately, it will guide our decisions on how to enhance customer satisfaction and engagement, shaping our strategic approach.

Analysis

Question 1

Can we decipher the core themes driving user sentiment towards Fanatics, as expressed both on Twitter and in reviews? Utilizing text mining techniques and visualization, we aim to pinpoint recurring topics and sentiments, unraveling the nuanced fabric of customer opinions to inform strategic insights.

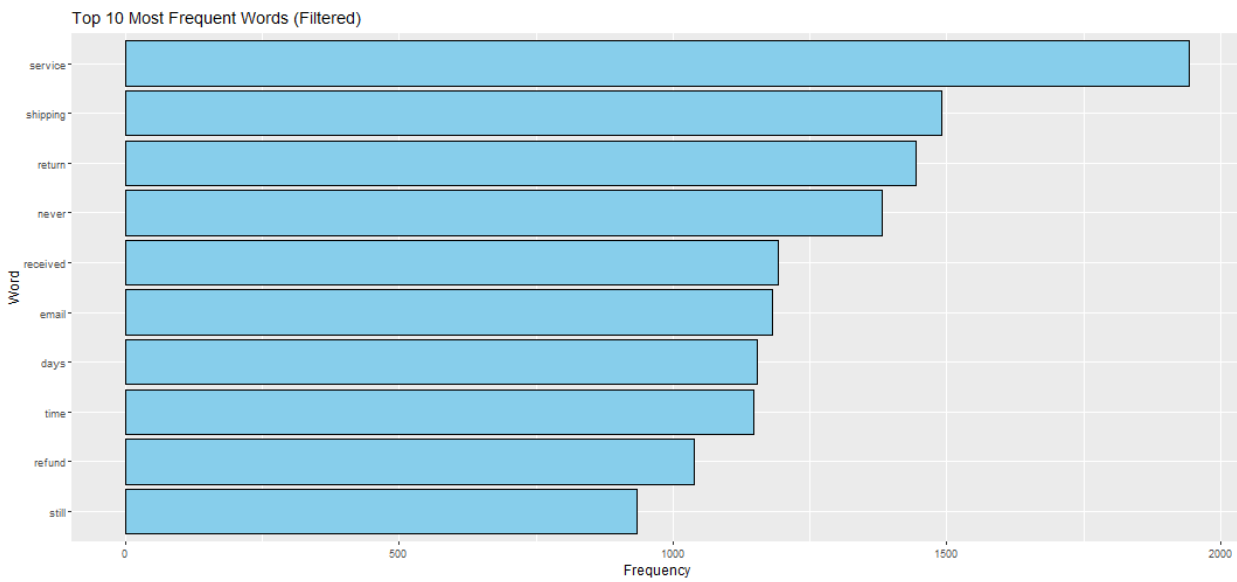
Figure 1

The initial word cloud provides insights into prevalent terms in customer reviews, emphasizing "service," "ordered," and "return", among others. Yet, beneath the surface, "cancel", "waiting", and "package" hint at concerns about delivery times and quality customer service. To unravel more detailed sentiments, our exploration extends to a two-word sequence word cloud. This strategic move aims to capture nuanced expressions and unveil precise phrases that contribute to the overall sentiment, setting the stage for a deeper analysis in the upcoming figure.

Figure 2

The second word cloud unfolds a deeper layer of customer sentiments, spotlighting the significant recurrence of "will never" that signals potential dissatisfaction or unmet expectations. The prominence of "customer service" as the largest word prompts an essential inquiry into the nature of sentiments associated with this aspect—whether positive or negative. Notably, phrases like "cancel order", "return policy", and "wrong size" echo persistently, indicating recurring challenges linked to order adjustments and fulfillment. This nuanced exploration sets the stage for a comprehensive analysis of specific customer concerns and preferences, aligning with our objective to unveil intricate sentiments.

Figure 3



The exploration of word frequencies in this discrete figure underscores the prevalence of key terms such as "service", "shipping", and "return", though it may be difficult to see. Notably, high-frequency occurrences of "never" and "received" point towards persisting challenges in these specific areas. The dominance of words primarily related to customer service and shipping concerns establishes a critical groundwork for the forthcoming sentiment analysis. This detailed examination unveils the focal points within customer reviews, providing valuable insights for a comprehensive understanding of sentiment dynamics.

Figure 4

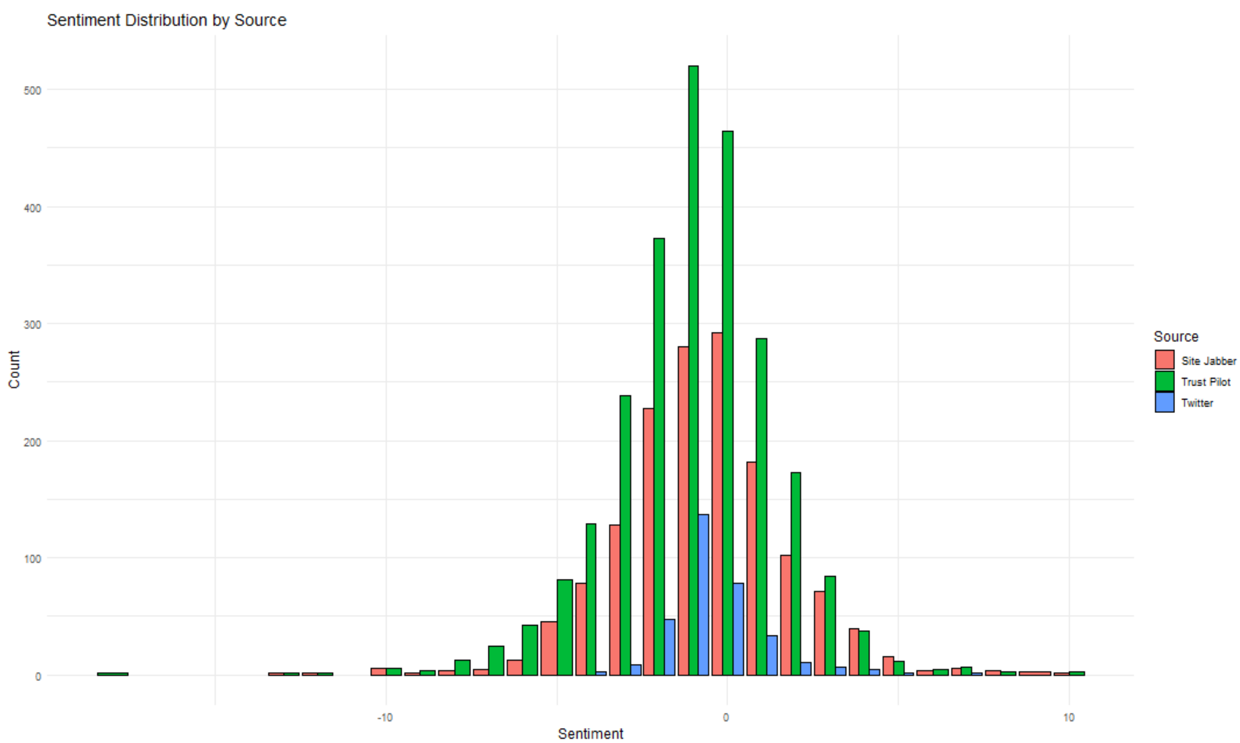
	Word	Average_Sentiment
1	service	-1.0435356
2	shipping	-0.9904051
3	return	-1.0729858
4	never	-1.1911632
5	time	-0.9431321
6	refund	-0.7035755
7	received	-0.8680258

Evaluating the average sentiment associated with key words unveils a consistent trend of negative sentiments. Notably, terms like "service," "shipping," and "return" demonstrate relatively low sentiment scores, reflecting a prevailing dissatisfaction in these particular aspects. This analysis emphasizes the significance of understanding the context in which these words are used, providing valuable insights into specific pain points and areas requiring improvement in the overall customer experience.

Question 2

To what extent do sentiments on Twitter align with the more in-depth opinions expressed in user reviews from web scraping? Our investigation aims to uncover the correlation between Twitter conversations and the sentiments articulated on review websites. This comparative analysis seeks to reveal any consistent patterns or divergences, offering valuable insights into the convergence of sentiments across different platforms.

Figure 5



Examining the sentiment distribution across sources, a prevalent trend emerges, highlighting an overall negative sentiment. The majority falls within the -1 to -4 range, with notable outliers dipping to extremely negative scores, underscoring the presence of strongly dissatisfied customers. Counterbalancing these negative sentiments, positive scores, though less frequent, persist, offering glimpses into areas where the company has managed to elicit satisfaction. The varying distribution of sentiments among Sitejabber, Trustpilot, and Twitter provides a nuanced perspective, paving the way for a detailed exploration of factors influencing user satisfaction and dissatisfaction across distinct platforms.

Figure 6

	Source	AverageSentiment
	<chr>	<dbl>
1	Site Jabber	-0.619
2	Trust Pilot	-0.939
3	Twitter	-0.502

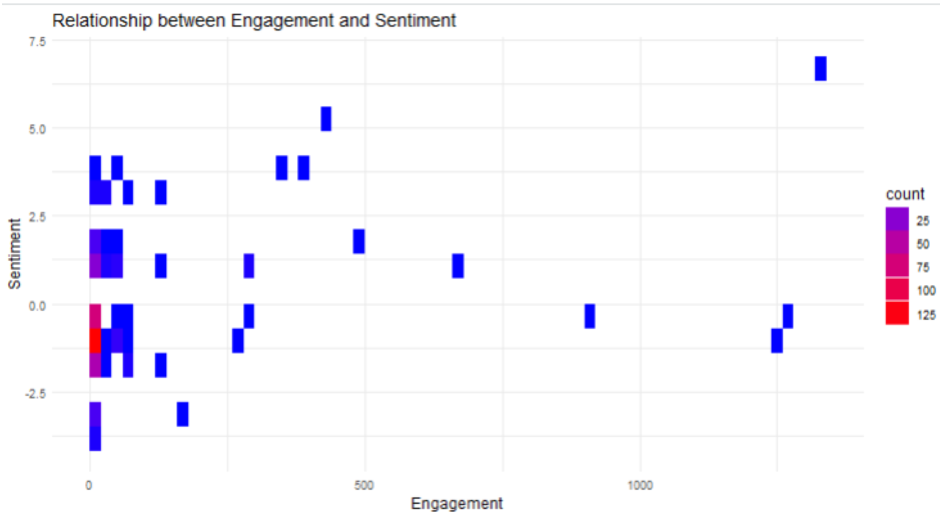
Diving into the realm of average sentiments across platforms unravels a spectrum of insights. Trustpilot stands out with the most negative sentiment recorded at -0.939, indicating a higher prevalence of dissatisfaction among users on this platform. In contrast, Twitter boasts a relatively higher average sentiment of -0.502, suggesting a potential shift in sentiment dynamics attributable to distinct user demographics or the nature of discussions within the microblogging platform. This variation in average sentiments among Sitejabber, Trustpilot, and Twitter contributes to a richer understanding of the diverse sentiment landscapes across different sources.

Figure 7

	AverageSentiment	AverageRating
1	-0.9388	1.5796

Diving deeper into the realm of average sentiments, the consistent narrative across Figures 6 and 7 is that Trustpilot consistently reports more negative sentiments compared to other platforms, as indicated by both sentiment scores and average ratings. This aligns with the overarching goal of understanding sentiment landscapes across different sources, providing valuable insights into factors influencing user satisfaction and dissatisfaction. We can only hypothesize that if there were ratings for Twitter and Site Jabber, the average rating would be above ~ 1.6, due to the correlation between sentiment and ratings.

Figure 8

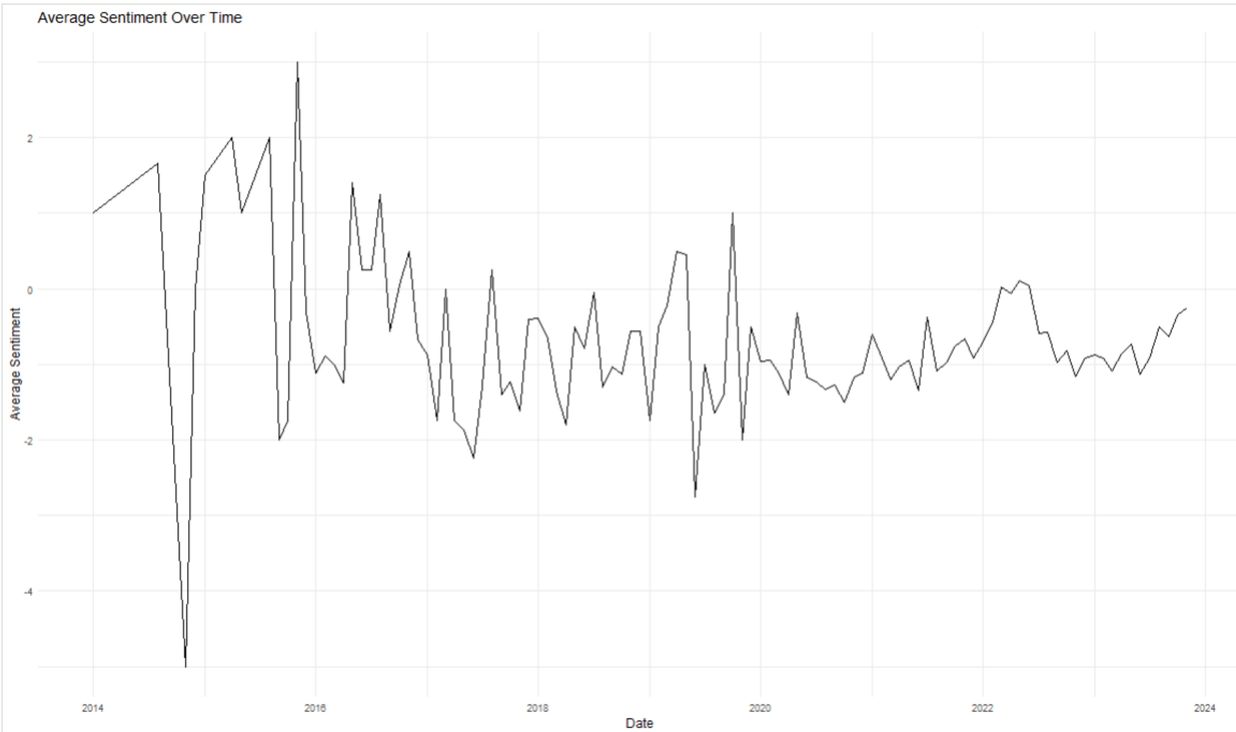


This heatmap investigates the interplay between engagement on Twitter, derived from the summation of likes and retweets, and sentiment. The analysis seeks to discern whether higher engagement correlates with more positive or negative sentiment. The predominant heat is observed in the -1-sentiment range, indicating little to no engagement. Remarkably high sentiment, around 6.5, aligns with engagement surpassing 1500. Additionally, other significant occurrences of engagement fall slightly below 0, emphasizing a variety of sentiments associated with different levels of engagement. This exploration of the relationship between engagement and sentiment provides a nuanced understanding of how user interactions on Twitter correspond with sentiments expressed. The more red dots in the heatmap visually emphasize areas with heightened activity, shedding light on potential patterns in sentiment dynamics.

Question 3

Our exploration into temporal sentiment trends poses the question: How do sentiments evolve over time, pinpointing specific months with notable shifts? Additionally, what events or influences underlie these temporal changes? Through time-series analysis, we aim to unearth the underlying narrative of sentiment dynamics, extracting valuable insights that contribute to a comprehensive understanding of user sentiments toward Fanatics.

Figure 9



The time series analysis unveils a notable negative sentiment spike in mid-to-late-2014, sparking a curiosity to unearth the root cause behind this significant shift in customer sentiments. The subsequent effective response from management is evident as sentiments gradually improve, eventually reaching positive territory in early 2015. While the overall trend exhibits a random walk, understanding the circumstances surrounding the mid-2014 spike presents a compelling case study. Uncovering the nature of this pivotal event offers valuable insights into the dynamic landscape of customer satisfaction, providing strategic guidance for proactive reputation management.

Conclusion

Derived Insights

The comprehensive analysis of user sentiments towards Fanatics, encompassing both Twitter and review platforms, has yielded valuable insights into the intricacies of customer opinions. From the core themes driving sentiments to the alignment of Twitter discussions with in-depth reviews, each facet offers a unique perspective on the customer experience. The examination of word clouds, sentiment distributions, and average sentiments has unraveled prevailing concerns related to customer service, shipping, and returns. These insights form a foundational understanding of the factors shaping user sentiments.

Actionable Recommendations

Customer Service Enhancement

The centrality of "service" in customer sentiments underscores the need for improvements. Implementing efficient issue resolution is vital, especially considering that customers actively reach out to customer service when facing challenges. Addressing concerns about order cancellations is crucial for maintaining customer trust. Enhancing overall customer service goes beyond issue resolution; it is about creating a positive and supportive interaction that fosters loyalty. As customer service is often the first point of contact for issue resolution, it plays a pivotal role in shaping the overall perception of Fanatics.

Shipping Optimization

Given the significance of "shipping" in user sentiments, optimizing shipping processes is paramount. Fanatics, known for its agile supply chain, should ensure that this reputation aligns with customer experiences. Providing accurate delivery estimates is critical in meeting customer expectations. Minimizing delays is not just about speed but about reliability. Ensuring that customers receive their orders on time and in good condition directly contributes to positive sentiment. Addressing issues with sizes and quality through shipping optimization enhances the end-to-end customer experience.

Feedback Utilization

Leveraging insights from Twitter, Trustpilot, and Sitejabber allows for targeted improvements. Platform-specific feedback provides a nuanced understanding of distinct concerns raised by users on each platform. This approach enables Fanatics to tailor responses and enhancements to address platform-specific pain points. By understanding the unique dynamics of each platform, Fanatics can enhance overall user satisfaction and adapt strategies to meet diverse user expectations.

Periodic Sentiment Monitoring

Ongoing sentiment monitoring, as highlighted by the time series analysis, is crucial for Fanatics. Regular assessments enable the identification of emerging trends, ensuring proactive interventions to maintain a positive brand image. Periodic sentiment monitoring not only captures the current state of sentiments but also allows Fanatics to adapt strategies swiftly in response to evolving customer preferences and market dynamics.

Root Cause Analysis

Investigating the root causes of historical sentiment spikes is a valuable learning opportunity. Understanding and addressing these causes can prevent similar issues in the future, contributing to sustained positive sentiments. By conducting root cause analyses, Fanatics gains insights into critical events that have shaped customer perceptions. This proactive approach ensures that Fanatics remains vigilant, learning from past challenges to enhance its reputation and maintain positive sentiment.

Limitations

While this study provides valuable insights, some limitations should be considered. The inclusion of advertisements in the Twitter data frame could impact the integrity of the relationship between engagement and sentiment (Figure 8). Additionally, time constraints may limit a deeper understanding of the time series effect in Figure 9. Delving into the root causes of sentiment fluctuations over time requires further investigation that is above our pay grade. Forward-looking, our future work could focus on refining sentiment analysis models, exploring more platforms, and incorporating advanced machine learning techniques for predictive insights.

Data Sources

Sitejabber
Trustpilot
Twitter

Resource Information

Power Automate Tutorial
RSelenium
Tidy Sentiment Analysis
TM Project
TM Methodologies
Twitter Scraping
Michael Colbert

Tool Sources

Docker Desktop
HAR Converter
Power Automate
JSON Validator
JSON Converter
RStudio