

SENTIMENT ANALYSIS – OPINION MINING FOR MARKET RESEARCH



Birla Institute of Technology and Science - Pilani

TITLE OF THE PROJECT –

A Comparative Analysis of Positive and Negative Sentiment in Wearable Tech Reviews

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COURSE- MBA in Business Analytics

TABLE OF CONTENTS

1. Abstract.....	1
2. Introduction.....	1
3. Objectives.....	2
3.1. Ingest Raw Data	
3.2. Filter Non-Critical Feedback	
3.3. Preprocess Review Text	
3.4. Summarize and Analyse Sentiment	
3.5. Deliver Actionable Insights	
4. Dataset Description.....	3
4.1. Redundant Columns	
4.2. Initial Inspection	
4.3. Filtering Focus	
5. Libraries Used.....	4
5.1. Core Libraries	
5.2. NLP & Text Preprocessing	
5.3. Summarization and External Tools	
6. Data Preprocessing.....	5
7. Exploratory Data Analysis.....	5
8. Insights & Observations.....	6
8.1. Review Summarization	
8.2. Observations	
8.3. Tone and Sentiment	
9. Conclusion & Summary.....	9
9.1. Key Accomplishments	
9.2. Final Thoughts	
10. References.....	10

Final Project Report

Sentiment Analysis - Opinion Mining for Market Research

1. Abstract

This market research project conducts a large-scale sentiment analysis and opinion mining study on over 330,000 Fitbit user reviews. The primary objective is to transform unstructured customer feedback into actionable market intelligence. By employing Natural Language Processing (NLP) and advanced topic modeling, this analysis identifies the core drivers of customer satisfaction and dissatisfaction within the competitive wearables market. Key findings indicate that while the brand's core strengths lie in its **motivational ecosystem** and **effective sleep tracking**, its market position is threatened by significant reliability issues, primarily **syncing failures** and **buggy software updates**. This report provides a data-driven view of the brand's competitive landscape, highlighting critical vulnerabilities and strategic opportunities for product improvement and market positioning.

2. Introduction

In the rapidly evolving wearable tech industry, customer feedback is a pivotal asset in shaping product development and refining the user experience. For a market leader like Fitbit, online reviews offer a direct and unfiltered channel to user insights. While 5-star reviews provide validation, it is within the 1- to 4-star ratings that customers often articulate specific issues, frustrations, and invaluable suggestions for improvement. However, manually analyzing this vast volume of unstructured text is neither scalable nor efficient.

This project introduces a robust data analysis pipeline designed to systematically mine these user reviews for actionable intelligence. By focusing on distinct user segments—the "Detractors" (1 and 2-star reviews) and the "Promoters" (4 and 5-star reviews)—this analysis uncovers the core drivers behind both customer dissatisfaction and brand loyalty.

The pipeline leverages Natural Language Processing (NLP) techniques, beginning with essential text cleaning, stop word removal, and TF-IDF vectorization to prepare the data for machine learning. The core of the analysis is conducted using **Non-Negative Matrix Factorization (NMF)**, a powerful topic modeling algorithm, to automatically identify and cluster the most significant recurring themes within both positive and negative feedback.

To ensure the accuracy and clarity of these findings, the statistically generated topics were then interpreted and subsequently verified using an AI language model (Google's Flan-T5). This two-stage approach combines the statistical rigor of topic modeling with the contextual understanding of modern AI, transforming thousands of individual reviews into a concise set of strategic insights. By turning unstructured feedback into a clear view of market pains and pleasures, this project demonstrates how NLP can effectively guide data-driven product strategy and innovation.

3. OBJECTIVE

The analysis is structured around several concrete objectives that are essential to extracting meaningful insights from a large set of unstructured reviews:

- **3.1. Ingest Raw Data:** To load and structure a large-scale dataset of over 330,000 raw customer reviews for analysis.
- **3.2. Filter Non-Critical Feedback:** To segment the market by isolating distinct user cohorts: "Detractors" (ratings 1-2) to identify key market pain points and churn risks, and "Promoters" (ratings 4-5) to identify core brand strengths and key value propositions.
- **3.3. Preprocess Review:** To implement a rigorous NLP preprocessing pipeline to clean and normalize the review text, ensuring high-quality input for accurate opinion mining.
This includes:
 - Removing HTML tags or non-alphabetic characters
 - Lowercasing all text
 - Removing stopwords
 - Tokenizing the text
- **3.4. Summarize and Analyse Sentiment:** To utilize NMF topic modeling to extract the most salient themes of praise and complaint. This was followed by a verification step using AI language models to translate the statistical findings into qualitative insights.
- **3.5. Deliver Actionable Insights:** To synthesize all findings into a strategic market research report detailing competitive vulnerabilities, core brand strengths, and unmet customer needs, providing a clear path for data-driven decision-making.

4. Dataset Description

The analysis was conducted on a public dataset of 333,491 Fitbit user reviews.

- **4.1. Redundant Columns:** To focus the analysis, non-essential columns (such as Unnamed: 0, source, review_title, and review_date) were dropped. These were not essential for the NLP tasks and were dropped to reduce complexity
- **4.2. Initial Inspection:** Using df.info() and df.head(), the dataset structure, null values, and data types were verified. The dataset was cleaned by removing 138 rows containing null review descriptions, resulting in a robust final dataset of 333,353 reviews for analysis.
- **4.3. Filtering Focus:** The core market research strategy involved analyzing two key customer segments separately to achieve a clear, unmixed signal for both positive(rating 4-5) and negative(rating 1-2) drivers of opinion.

5. Libraries Used

A combination of industry-standard Python libraries for data science and specialized NLP tools were employed.

5.1. Core Libraries:

- **pandas:** For all data ingestion, structuring, and manipulation tasks

5.2. NLP & Text Preprocessing:

- **nltk:** For foundational NLP tasks like tokenization, stop word removal, and N-gram analysis.
- **re (regex):** For cleaning and normalizing raw text data.
- **scikit-learn:** For implementing the machine learning pipeline, including `TfidfVectorizer` for feature engineering and NMF for topic modeling.
- **spaCy:** Utilized in the verification phase for Named Entity Recognition (NER) to identify competitor mentions.

5.3. Summarization and External Tools:

- **transformers:** The Hugging Face library was used to run the `google/flan-t5-large` model to verify the interpretation of topic model outputs.
- **VADER Sentiment:** Used in verification to generate nuanced sentiment scores, confirming the polarity of the filtered review subsets.

6. DATA PREPROCESSING

Before extracting insights, it was essential to clean and normalize the textual review data. Text preprocessing ensures that the NLP model operates on meaningful input, free of noise and irrelevant components.

6.1. Text Cleaning - The cleaning process uses regular expressions to remove unwanted characters. The core steps included:

- Removing HTML tags or numeric characters.
- Replacing punctuation with spaces.
- Converting text to lowercase to ensure uniformity.
- Removing special symbols or formatting artifacts.

6.2. Stopword Removal - Stopwords are removed using NLTK's pre-defined English stopwords list (using a custom list to filter out domain-specific noise like "fitbit", "app"). This reduces redundancy and emphasizes content-specific words (e.g., "battery," "sync," "support").

6.3. Tokenization - Each review is split into individual words (tokens), which are the smallest units of text analysis. These are stored for subsequent processing, such as summarization or sentiment tagging.

6.4. Creating Clean dataset - The cleaned dataset was saved for future use and loaded again for further analysis and modelling.

7. Exploratory Data Analysis

Exploratory Data Analysis plays a critical role in identifying underlying patterns, anomalies, and trends before proceeding with advanced text processing. Initial EDA provided a high-level market overview and identified preliminary trends.

- **7.1. Star Rating Distribution:** The mean rating of **3.29** revealed a polarized market perception, with a significant volume of both highly satisfied and highly dissatisfied customers. 1- and 2-star reviews provided the most critical feedback, often containing strong language and specific complaints about product failures or service gaps.
- **7.2. Word Frequency Patterns:** N-gram analysis of negative reviews (1- and 2-star reviews) served as a powerful leading indicator. The overwhelming frequency of phrases like **please fix** and **since last update** immediately flagged product stability and software updates as major areas of concern in the market.
- **7.3. Sentiment Distribution using VADER:** A VADER sentiment analysis confirmed the strong negative polarity of 1 and 2-star reviews and the strong positive polarity of 4 and 5-star reviews, validating the market segmentation strategy.

8. Insights & Observations

The core market intelligence was derived from a detailed analysis of the topics discovered within the positive and negative user segments.

8.1. Review Summarization: NMF topic modeling was used to identify the top 5 themes for both market "Detractors" and "Promoters." These themes were then interpreted to provide qualitative insights.

8.2. Observations:

- **Key Market Pain Points (Issues from Detractors):**
 - **Syncing & Connectivity:** The number one issue driving customer churn. Users express immense frustration with the product's inability to reliably sync with their phones.
 - **Software Instability:** Software and firmware updates are perceived as a major risk, often cited as the direct cause of a device "breaking" or losing functionality.
 - **Core Function Failure:** A significant portion of complaints centered on the failure of fundamental features, such as inaccurate step/sleep tracking, devices no longer charging, and broken notifications.

Topic 1

Keywords: [sync, connect, won't, phone, Bluetooth, connection, issues, tried, problem, pair, constantly, restart]

Interpretation: unable to sync with phone or bluetooth constantly disconnects and restarts

Topic 2

Keywords: [stopped, working, notifications, properly, time, months, fine, ago, worked, charge, screen, longer]

Interpretation: a fitness tracker stopped working properly and notifications stopped working for months

Topic 3

Keywords: [steps, tracking, track, sleep, heart, rate, data, count, accuracy, doesn't, accurate, calories]

Interpretation: a fitness tracker that doesn't count steps and calories accurately.

Topic 4

Keywords: [update, latest, new, version, firmware, after, since, broke, worked, fix, recent, useless]

Interpretation: useless fitness tracker broke after latest firmware update.

Topic 5

Keywords: [customer, service, support, bad, experience, premium, pay, useless, features, time, money, waste]

Interpretation: bad customer service and support for a fitness tracker

• Core Brand Strengths (Praises from Promoters):

- **Motivation & Engagement:** The product's ability to motivate users through goal tracking and reminders is its most powerful competitive advantage and a key driver of brand loyalty.
- **Sleep Tracking Excellence:** The sleep tracking feature is universally praised for its detail and insights, representing a core pillar of the positive brand experience.
- **User-Friendly Interface:** A significant user segment values the product for being easy to set up and understand, lowering the barrier to entry for new customers.

Topic 1

Keywords: [love, keeps, track, sleep, fit, helps, steps, bit, motivated, day, absolutely, charge]

Interpretation: keeps track of your steps, sleep, and sleep cycle to help you stay fit and motivated throughout the day

Topic 2

Keywords: [great, works, track, fitness, tracking, tool, sleep, way, far, motivator, product, steps]

Interpretation: great tool for tracking your steps and sleep and a great way to motivate yourself

Topic 3

Keywords: good, far, really, works, pretty, like, track, sleep, health, tracking, overall, steps

Interpretation: good far really works pretty like tracking sleep health overall

Topic 4

Keywords: [easy, track, keeps, helpful, really, like, set, excellent, understand, motivated, helps, sleep]

Interpretation: easy to use and keeps track of your workouts and sleep

Topic 5

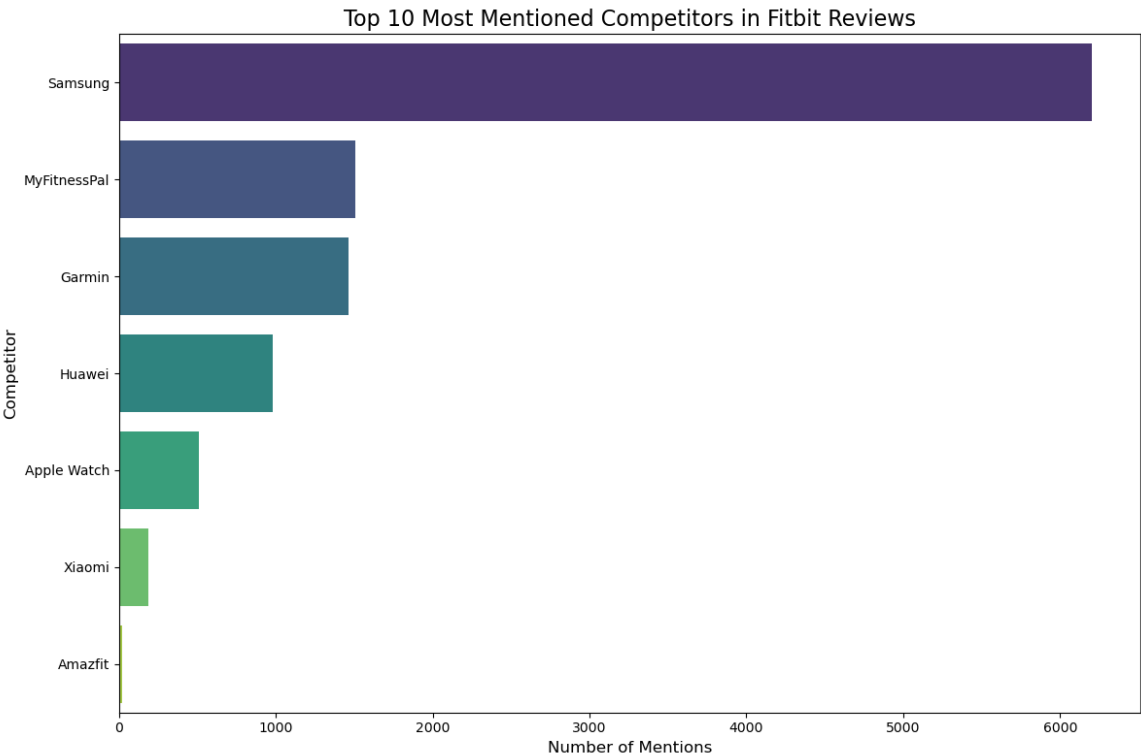
Keywords: [awesome, track, keeps, sleep, helps, fitness, works, really, motivated, steps, like, fit]

Interpretation: awesome fitness tracker keeps you motivated and keeps you fit

- **Competitive Landscape Analysis (The Risk of Churn)**

To quantify the market risks posed by the issues above, an analysis was performed to identify mentions of competing brands within the reviews.

- **Primary Threats Identified:** The analysis of 10,567 competitor mentions revealed that **Samsung** (6,202 mentions), **Garmin** (1,466 mentions), and **Apple Watch** (508 mentions) are the most frequently cited competitors.



- **Context of Mentions:** The average rating of reviews mentioning hardware competitors like Amazfit (1.47 stars), Garmin (1.71 stars) and Apple Watch (2.00 stars) was extremely low. This provides strong evidence that these brands are not merely being compared but are being actively considered as replacements by highly dissatisfied customers who are looking to switch. **Ignorance may lead to losing customers**, as they have clearly indicated their willingness to switch to more reliable competitors.

Average Rating of Reviews When a Competitor is Mentioned:		
	competitors_mentioned	rating
0	Amazfit	1.476190
1	Xiaomi	1.682796
2	Huawei	1.703364
3	Garmin	1.708049
4	Apple Watch	2.000000
5	Samsung	2.106579
6	MyFitnessPal	3.600664

8.3. Tone and Sentiment: The sentiment analysis revealed a deep market polarization. Detractors used language of finality and frustration (useless, waste of money), while promoters used emotive and loyal language (love, awesome, motivator), indicating that the product experience is either extremely positive or extremely negative, with little middle ground.

9. Conclusion & Summary

9.1. Key Accomplishments:

- This project successfully analyzed over 330,000 unstructured user reviews to extract clear, data-driven business intelligence.
- It systematically identified and prioritized the most critical product issues affecting Fitbit users, confirming that **syncing failures** and **unreliable software updates** are the primary drivers of negative sentiment.
- It clearly defined the core brand strengths that foster customer loyalty: **effective motivation, reliable sleep and activity tracking**, and a **user-friendly interface**.
- Through competitive analysis, it quantified the significant business risk posed by customer churn, identifying **Garmin, Apple Watch, and Samsung** as the primary beneficiaries of Fitbit's reliability issues.

9.2. Final Thoughts

This analysis reveals a stark "tale of two products." When the core functionalities of tracking and syncing are reliable, customers become passionate brand advocates who feel motivated and supported. However, when these fundamental features fail—particularly after a software update—the user experience collapses, leading to extreme frustration and brand abandonment.

The message from the market data is unambiguous. The user base is not primarily demanding new or revolutionary features; they are demanding a product that is **functional and reliable**. The most critical, data-driven recommendation from this report is for the business to shift its focus from feature expansion to core product stabilization. Investing in a robust syncing architecture and a more rigorous quality assurance program for software updates is not merely a technical fix—it is an essential business strategy.

The findings presented here are a direct reflection of the customer's voice. **Ignorance may lead to losing customers**, as they have clearly indicated their willingness to switch to more reliable competitors. Addressing these foundational issues is the most direct path to improving customer satisfaction, reducing churn, and protecting the brand's long-term health in a competitive market.

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