Enhancing Diabetes Care

Unveiling Continuous Glucose Monitoring Perspectives and Product Insights through Social Media Analytics

Data Science for Product Managers

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Executive Summary

- CGM devices offer continuous monitoring of glucose levels, providing real-time data to help diabetes patients manage their condition more effectively.
- Patients seek improved accuracy, ease of use, better integration with wearable technology, reduced sensor errors, longer sensor lifespans, and better affordability.
- Users appreciate Dexcom's accuracy, integration with smart devices, real-time monitoring, reliability and automated insulin dosing.
- Common complaints from Dexcom include sensor inaccuracies, adhesion issues, occasional false alarms, the need for frequent calibrations, limited smartwatch compatibility, and high costs.
- Users recommend Freestyle Libre's ease of use, longer sensor life, reduced invasiveness (no fingersticks), affordability compared to other CGMs
- Common complaints involve occasional sensor errors, issues with sensor adhesion, lack of real-time alerts, less accuracy during rapid glucose changes, and the need for a separate reader

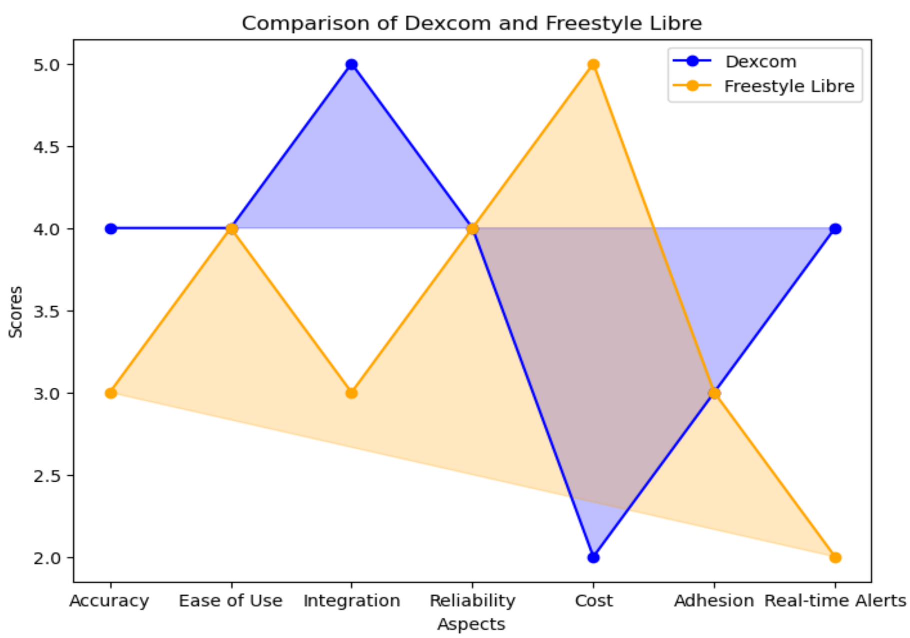

Figure 1: Radar Chart comparing aspects of Freestyle Libre and Dexcom

1. Introduction

1.1. Overview of the project

The project is designed to conduct a comprehensive analysis of Continuous Glucose Monitoring (CGM) devices using a dataset obtained from a diverse range of social media sources. The dataset provides a substantial sample size, comprising over 37,000 social media posts. The primary field within the dataset, contains text excerpts related to CGMs, providing user-generated feedback, experiences, concerns, and recommendations. Text data from social media can contribute towards product development and analysis. It provides an unfiltered, real-time sense of user feelings, preferences, and experiences, acting as a source of valuable information. Analyzing social media content offers an unprecedented avenue to comprehend consumer behaviors, identify emerging trends, and gauge market reception. Product managers can use this data to better understand the customer needs and pain points owing to the abundance of user-generated data available. This information helps in creating customised solutions and improving product offerings.

1.2. Objectives and goals

The text data served as a vital resource offering unfiltered insights into consumer sentiments, preferences, and challenges related to CGM devices. Analysis of the data facilitated the understanding of user perspectives, enabling informed decision-making for product enhancement and innovation. The project aims to utilize data science technique to understand customer perspectives and generate recommendations for product improvements. The utilization of this data was mostly focused around the following scenarios:-

- Extract Insights and user engagement metrics: Uncovering hidden patterns, common themes, and user sentiments from the social media dataset to understand user experiences with Dexcom and Freestyle Libre.

- Identify Pain Points: Identify and prioritize the key issues and challenges faced by users concerning sensor usability, cost, connectivity, accuracy, and other functionalities of CGM devices.

- Quantify Sentiments: Develop a sentiment analysis framework to quantitatively assess user sentiments towards Dexcom and Freestyle Libre, providing a comparative analysis of positive and negative feedback.

- Recommendation Generation: Formulating actionable recommendations from data-driven insights to address user concerns and improve the overall user experience with CGM devices.

- Enhance Product Features: Provide actionable insights that can be translated into specific improvements for Dexcom and Freestyle Libre.

1.3. Scope and methodology

In order to generate actionable insights from the data, numerous data science techniques have been utilized.

- Comprehensive Data Analysis: Conducted exploratory data analysis (EDA) to gain insights into user sentiments, concerns, social media engagement metrics, temporal evolutions and experiences related to CGM devices from the provided dataset.

- Topic Identification and Sentiment Analysis: Employ unsupervised learning model topic modeling techniques using Latent Dirichlet Allocation to unearth major themes in the data.

- Sentiment Analysis: Fitting a vader model to understand sentiments expressed in social media posts regarding Dexcom, Freestyle Libre and general glucose monitoring aspects.

- Machine Learning Application: Utilize machine learning models (such as Random Forest, Decision Trees, and SVM) to predict sentiment and gauge user satisfaction towards CGM devices based on social media posts.

- Recommendation Generation: Derive actionable recommendations for product enhancement strategies for Dexcom and Freestyle Libre based on the analysis, addressing identified user concerns and preferences.

- Large Language Models: Integration of LLMs towards generating powerful recommendations.

2. Literature Review

2.1. CGM devices in Diabetes care

Continuous Glucose Monitoring (CGM) is pivotal in transforming diabetes care by offering real-time insights for an individual's blood glucose levels. Its significance stems from several crucial aspects that greatly impact the management and quality of life for individuals dealing with diabetes [1]. The are some major ideas emphasising the role that CGM plays in the treatment of diabetes include:-

- **Real-Time Monitoring and Visibility:** CGM systems provide continuous, real-time monitoring of glucose levels, along with offering a comprehensive view of fluctuations throughout the day. The immediate visibility helps individuals understand how their activities, meals, medications, and stress levels impact their blood sugar levels.

- **Improved Treatment Decisions:** By providing real-time data, CGMs empower individuals and healthcare professionals to make informed decisions about insulin dosage adjustments, diet modifications, and lifestyle changes. This helps in managing hyperglycemia (high blood sugar) and hypoglycemia (low blood sugar) effectively.

- **Trend Analysis and Pattern Recognition:** CGM devices enable the identification of trends and patterns in glucose levels, assisting users in recognizing factors that influence their blood sugar. This information allows for proactive adjustments in treatment plans to achieve better glycemic control.

- **Reduced Need for Fingerstick Tests:** CGM systems minimize the necessity for frequent fingerstick tests, offering a less invasive and more convenient way to monitor glucose levels. This reduction in finger pricks enhances user comfort and compliance with regular monitoring.

- **Prevention of Long-Term Complications:** Maintaining stable blood sugar levels is crucial in preventing diabetes-related complications such as cardiovascular diseases, kidney problems, nerve damage, and vision issues. CGM devices aid in achieving better glycemic control, potentially reducing the risk of these complications.

- **Personalized Diabetes Management:** CGM systems allow for personalized diabetes management by catering to individual needs. They provide insights into how each person responds uniquely to various factors, enabling tailored treatment plans for optimal control.

- **Early Detection of Trends and Patterns:** CGM's ability to detect trends and patterns in glucose levels early on helps in anticipating and averting potential crises, making it a valuable tool for both users and healthcare providers.

2.2. Current market landscape and major players

With several prominent players competing for market share in Glucose Monitoring devices, Dexcom and Freestyle Libre stand out as key competitors in the diabetes care technology sector. Dexcom is positioned as a leader in CGM technology. It offers innovative devices like Dexcom G6 known for its accuracy, real-time alerts, and seamless integration with smart devices. Dexcom's continuous innovation and focus on user-centric features have strengthened its position as a top contender in the CGM market.

On the other hand, Freestyle Libre has substantial growth in the CGM landscape. Its user-friendly interface, longer sensor life, and cost-effectiveness compared to other devices in the market has garnered attentiog among the users.

A few other competitors alongside Dexcom and Freestyle Libre include Medtronic, which has been a longstanding player in the CGM landscapre. Additionally a few other companies like Senseonics, Eversense, and Medtrum are also contributing to the the CGM market with their respective product offerings. [2][3]

3. Data Collection and Preprocessing

3.1. Data cleaning and preprocessing techniques employed

The preprocessing of data involved a series of essential techniques applied to ensure the dataset's quality and readiness for analysis.

- Bag of Words model: Initially, a bag-of-words model was implemented using the Count Vectorizer method, which facilitated the conversion of unstructured text data into a structured ormat for further analysis

- Stop Words and Punctuation Removal: Removed stop words (commonly used words like 'the', 'and', etc.) and punctuations to refine the dataset, eliminating irrelevant elements and ensuring a more focused analysis.

- Tokenization: Used to break down the unstructured text data from social media posts into individual words or tokens, enabling the segmentation of sentences or phrases into analyzable units.

- Lemmatization: Applied to normalize words in the text data to their base forms, aiding in reducing words to their dictionary forms to minimize redundancy and ensure consistency in analysis.

- Part-of-Speech (POS) Tagging: Employed to categorize words in the social media text data into their respective parts of speech (nouns, verbs, adjectives, etc.), allowing for the identification and isolation of different linguistic elements for deeper analysis based on their syntactic roles.

- Handling Right Censoring: Noted the presence of right censoring in the dataset and intentionally retained this information rather than filtering it out, considering potential valuable insights embedded within.

- Construction of Document Matrix: Utilized the processed text data to construct a document matrix, preparing the dataset for in-depth analysis.

- N-gram modelling: This process involved combining consecutive words in the text to form sequential bigram and trigram word combinations.

4. Exploratory Data Analysis (EDA)

4.1. Engagement Metrics

The exploratory data analysis was used into assessing the frequency and distribution of posts across various social media platforms related to CGM devices. Reddit emerged as the platform with the highest frequency of posts, surpassing other platforms significantly, with Twitter trailing as a distant second. A notable trend observed was that the most common posts from specific users predominantly originated from Reddit, indicating a higher user engagement and participation within this platform.

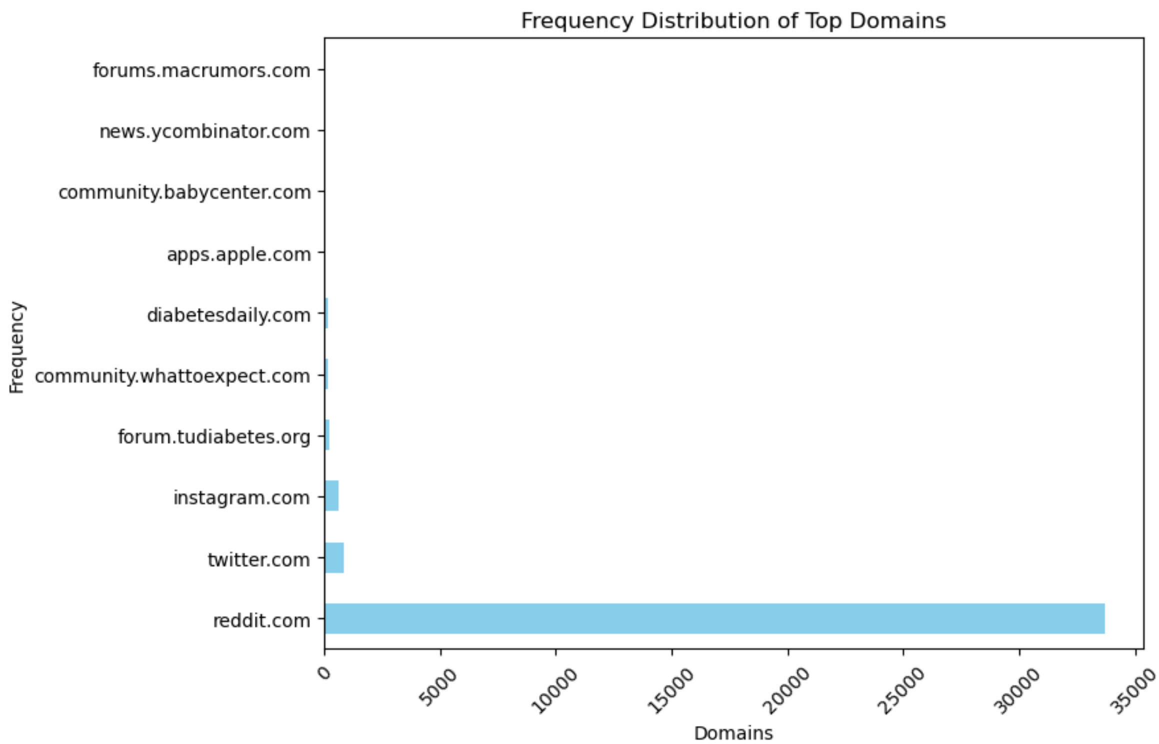

Figure 2: Most commonly used social media platforms discussing GCMs

Forums, as a social media platform, demonstrated dominance concerning discussions to other platforms such as blogs, tweets, Instagram, and similar channels. This preference for forums indicated a concentrated user interest in utilizing these spaces for more extensive discussions, exchanges, and information sharing about CGM devices.

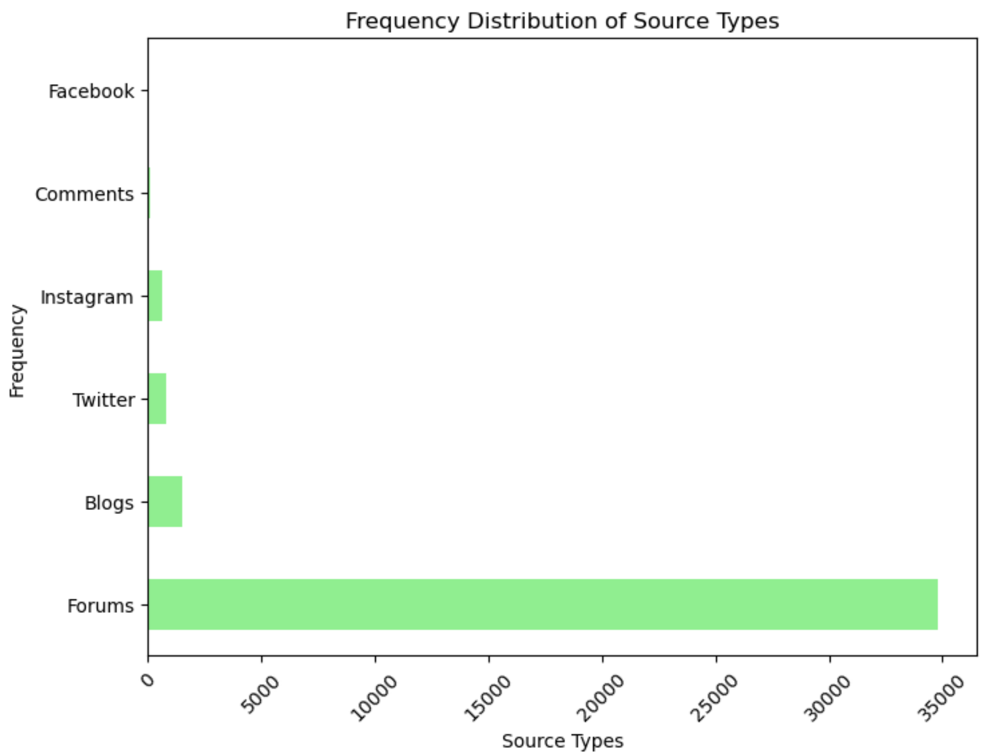

Figure 3: Most commonly used types of sources for GCM discussions

An analysis on the frequency of posts showed that the user activity remains stable through the year with some notable suges in specific time periods. It was observed that the activity notably surges in posting activity during the months of December and January.

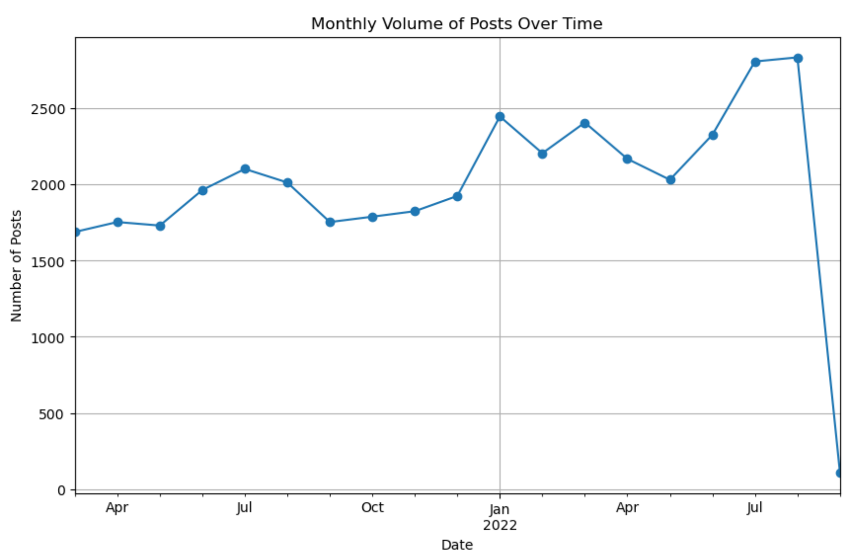

Figure 4: Volume of posts over time (right censored)

These spikes coincided with the holiday season and insurance renewal periods, signifying a surge in user engagement during these times. The increased activity can be attributed to users seeking information, sharing experiences, or encountering specific issues related to insurance renewals or addressing health concerns during festive periods. An analysis of the top most active user contributions to the data was mostly dominated by users of reddit with twitter being a distant second.

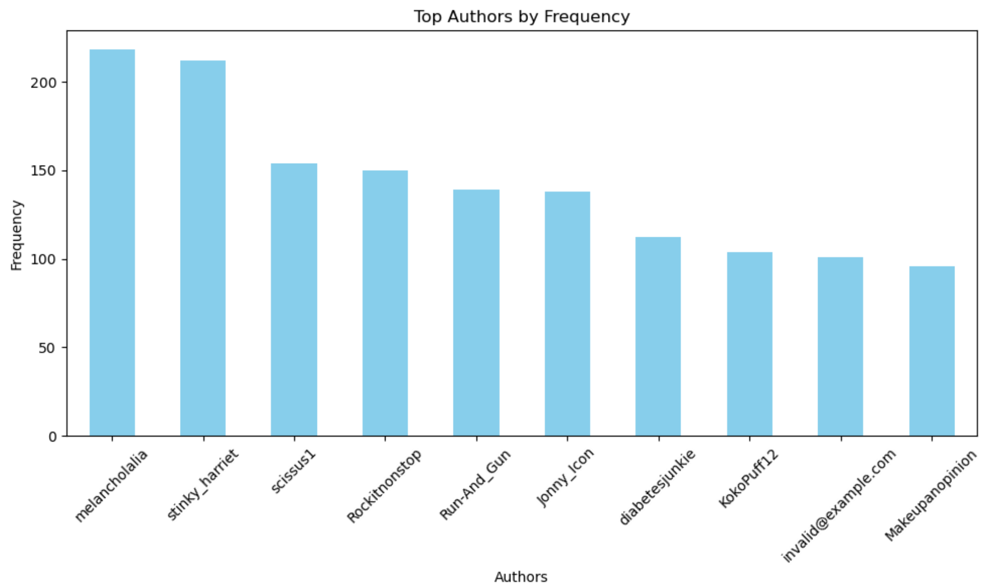

Figure 5: Top contributing authors

The analysis of engagement metrics across various social media platforms revealed Reddit's significance in user engagement and forums as preferred discussion spaces. It can be observed that Reddit is a platform that very actively talks about Glucose Continuous Monitoring and can be monitored to collect actionable data for generating insights.

4.2. Topic Modelling

Latent Dirichlet Allocation (LDA), an unsupervised learning model was employed as a topic modeling technique to uncover prevalent themes and discussions within the social media text data. The LDA model was fitted to the dataset, aiming to unveil underlying topics by identifying word patterns and co-occurrences across the text corpus.

Determination of Optimal Number of Topics:

To determine the optimal number of topics, a range of values from k=2 to 20 was assessed using an average coherence measure. Coherence measures the interpretability and semantic similarity of words within each identified topic. This process allowed for the selection of the number of topics that provided coherent and distinct themes present within the dataset. The whole process involves choosing between different occurrences of topics based on probabilistic word distributions.

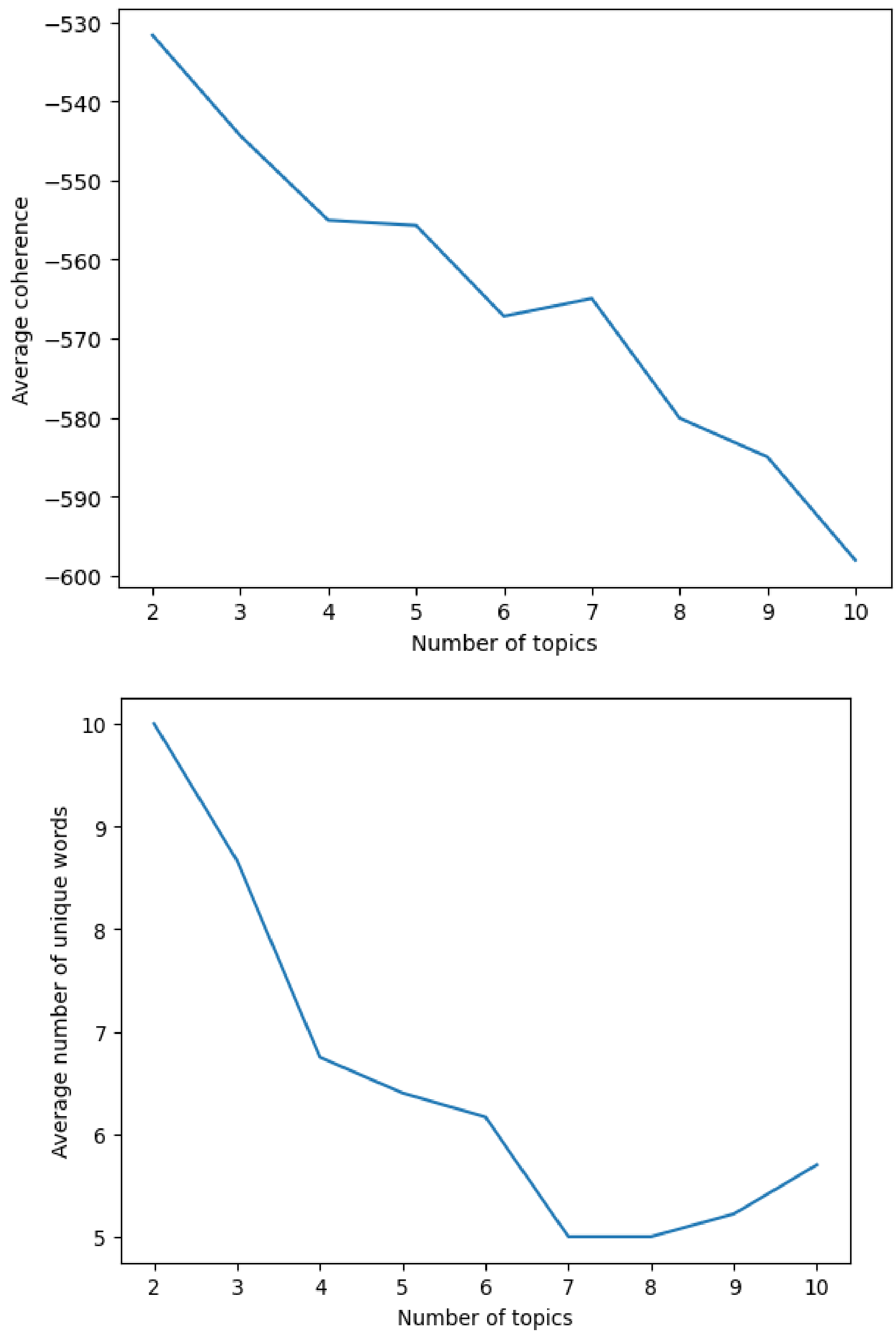

Figure 6: Iteratively comparing number of topics

If we analyse, the average coherence measures, it appears that k=2 would be an ideal choice. However, when we analyzed the distribution of top keywords based on their probabilities of occurrence, there was a lot of gibberish. So the idea behind LDA topics involves identifying a tradeoff between the coherence, overlapping topics and ensuring we get a good set of topics to base our analysis on.

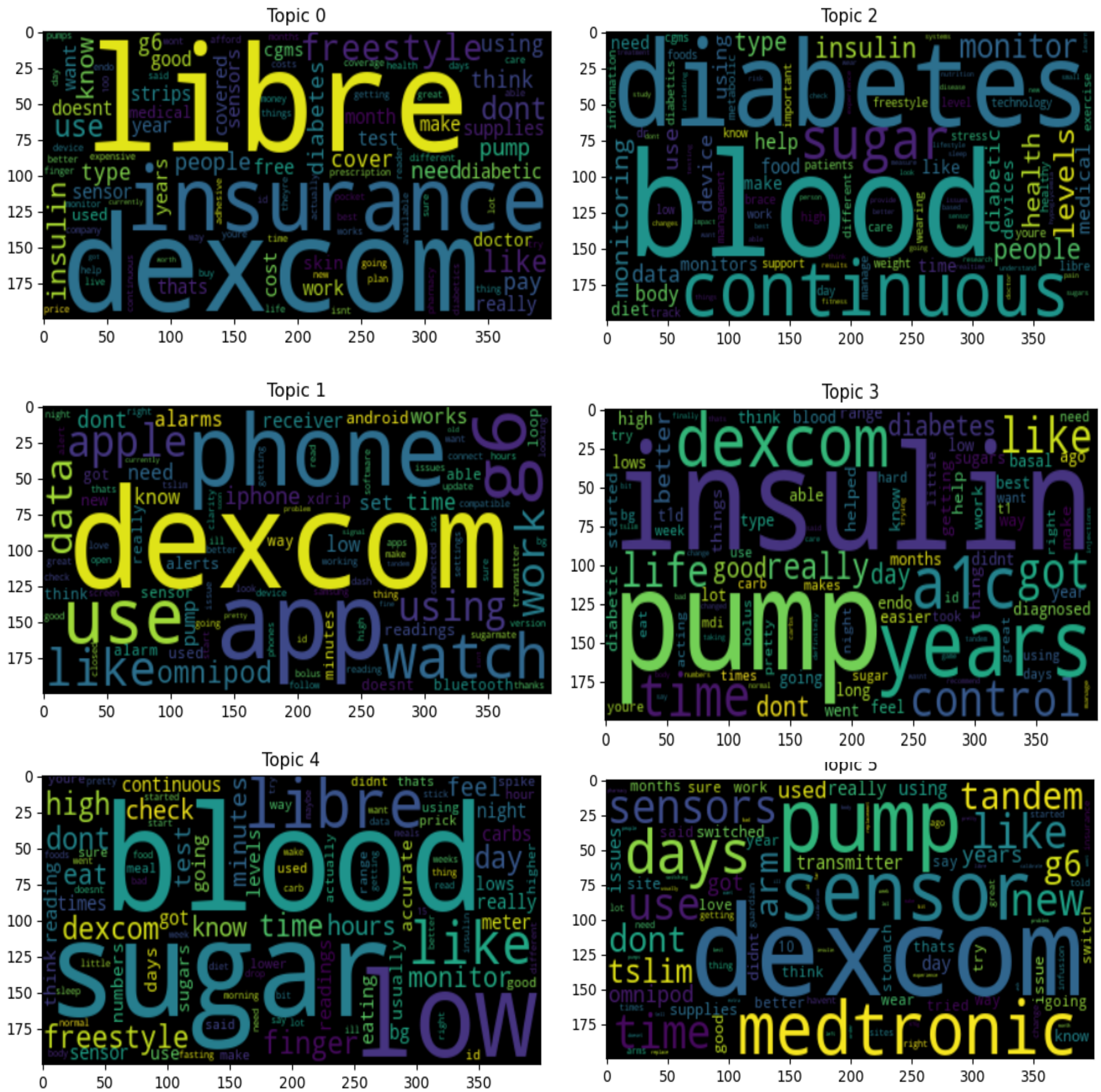

Figure 7: Wordclouds for different topics

Following the application of the LDA model, distinct topics emerged from the data. Each topic was characterized by a set of commonly occurring words based on their probabilities within the respective topic. Notable topics extracted from the analysis included:

- **Topic 0** - Insurance and User Concerns: Discussions encompassed insurance coverage issues, user experiences, and concerns regarding device usage.

- **Topic 1** - App, Devices, and Tools: Focused discussions on the Dexcom app, phone compatibility, and device usability.

- **Topic 2** - Health Monitoring and Diabetes Management: Centered around health monitoring, diabetes management, continuous glucose monitoring, and insulin levels.

- **Topic 3** - Insulin Pump and Diabetes Control: Addressed sentiments related to insulin pumps, diabetes control, and managing A1C levels.

- **Topic 4** - Blood Sugar Monitoring Challenges, Reliability: Engaged in discussions regarding challenges in blood sugar monitoring, device reliability, and monitoring difficulties.

- **Topic 5** - Device Comparisons and New Implementations: Explored comparisons among different devices, sensor usage, and mentions of various brands or implementations in diabetes management.

The identified topics reflected prevalent themes and discussions within the social media dataset, providing a structured understanding of diverse perspectives and concerns among users regarding CGM devices in diabetes care.

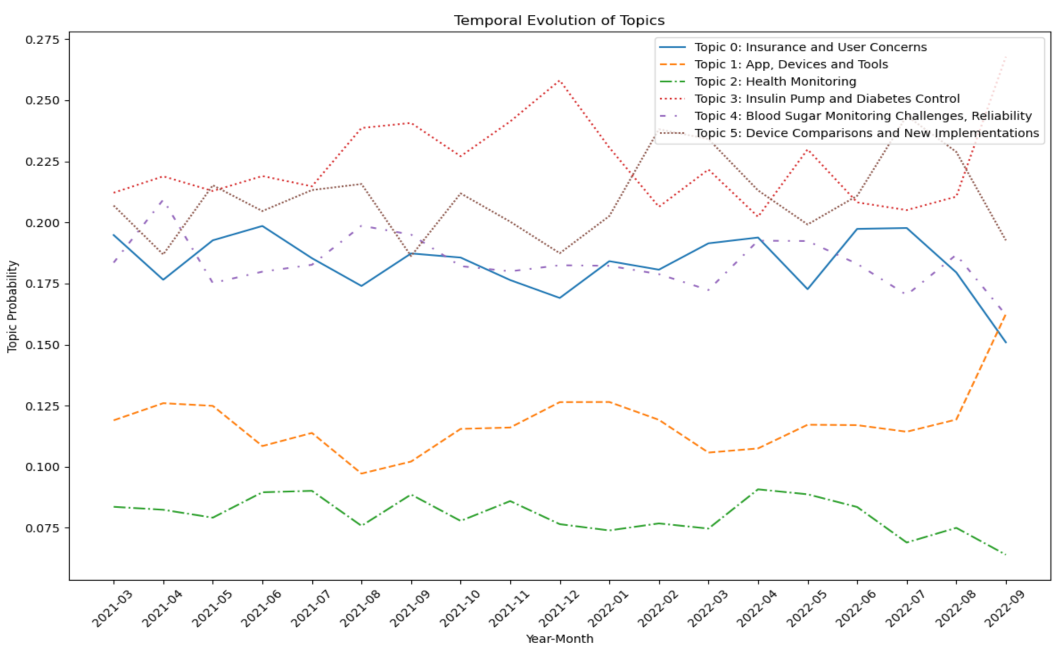

Figure 8: Temporal evolution of topics

The temporal evolution of topics offers valuable insights into how discussions regarding the different topics evolve over time. Diabetes control and insulin pump discussions are most commonly discussed topics. A number of customers also discuss about different devices and how freestyle libre and dexcom compare to these. There are considerable peaks for this topic at certain time periods and one reason behind it could be the release of a new product in the market. Monitoring how discussions around product-specific topics change over time provides insights into the reception and impact of product changes.

4.3. Sentiment Analysis

Utilizing a sentiment analysis model like VADER to assign sentiment scores on a scale of 1-5 provides a structured way to quantitatively measure the polarity of sentiments expressed within the text data. However, despite the presence of a pre-computed column with sentiment scores in the dataset, certain reasons might have led to the decision of not using this pre-existing sentiment column. Some considerations taken into account before proceeding with building a separate sentiment analysis model is as follows:-

- **Methodological Differences:** The pre-computed sentiment scores might have been derived using a different sentiment analysis technique or model that could yield varying results compared to the VADER sentiment analysis model. In order to ensure consistency of methodology for our analysis, it was essential to build our own model.

- **Granularity:** With our own model, we can offer a more nuanced understanding of the sentiments. If generalized into a 1-5 scale, it can capture the depth of sentiments present in the text data more effectively.

Additionally, to test our sentiments we have also implemented a few machine learning techniques to generate product recommendations based on the features that will help us understand how customers tend to feel.

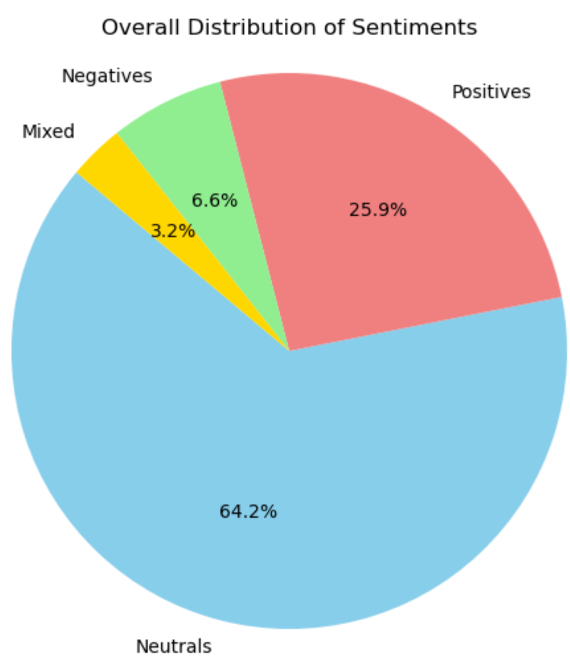

Figure 9: Sentiment Analysis over all GCM Discussions

Figure 10: Wordcloud for Specific Sentiment Ratinfs

Analyzing the data in the earlier stages based on the positive and negative sentiments helped understand a bit more about the general trends throughout the dataset. However, it was only through POS tagging that some semantic context was established in the data which helps generate more understanding of the product. Given below is a word cloud of commonly occurring words after POS-tagging.

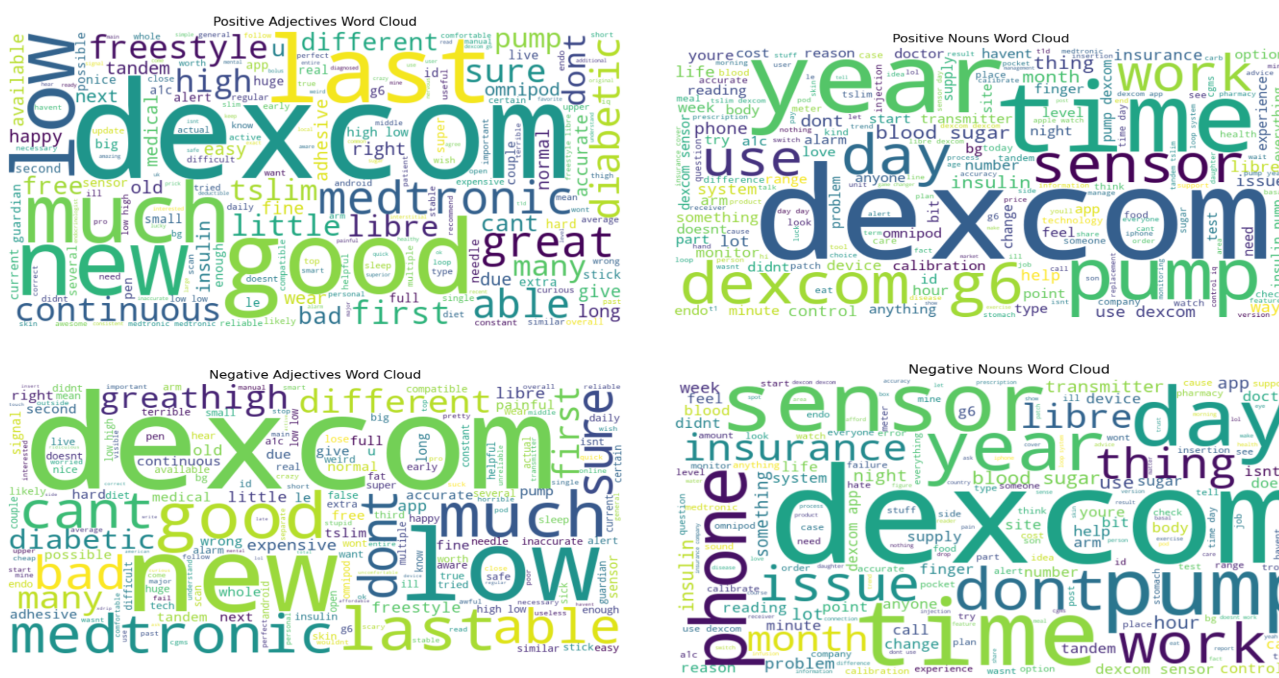

Figure 11: Wordclouds after POS-tagging(sampled for Dexcom sound bites)

5. Machine Learning Models

The sentiment classification task involved the utilization and analysis of three machine learning algorithms namely Random Forest, Decision Trees, and Support Vector Machines (SVM). Each model was implemented to classify sentiments expressed in the text data on a scale of 1-5.

5.1. Overview of machine learning models used

- Random Forest: Offers an ensemble learning capability, aggregating multiple decision trees to enhance accuracy and mitigate overfitting.

- Decision Trees: Offers simplicity in interpreting results and their ability to handle nonlinear relationships within the data.

- Support Vector Machines (SVM): Effective in handling high-dimensional data and its capability to identify complex decision boundaries for sentiment classification.

5.2. Performance evaluation and accuracy of each model

The different models were analyzed for the performance measures to uncover some important metrics of measurement. Here, the machine learning models were used as an additional step in ensuring that we get better insights about our sentiments. The sentiment rating score that was generated using the vader model on a scale of 1-5 was used as an input. Some observations from this analysis are:-

- The Random Forest model achieved an accuracy of approximately 70%, demonstrating robust performance compared to other models.

- Decision Trees showcased an accuracy of around 63%, highlighting reasonable classification capability but with slight limitations compared to Random Forest.

- Support Vector Machines (SVM): Reported an accuracy of approximately 58%, displaying comparatively lower performance due to challenges in handling overlapping classes within the sentiment classification task.

At first, the overall accuracy of the model was quite low. Deliberate adjustments were made to the test and sample sizes through oversampling and undersampling. These were aimed to address potential issues related to class imbalances, where one class was significantly outweighing the other in the dataset.

6. Key Findings and Insights

6.1. Major insights gathered from data analysis

The data analysis unearthed critical insights and trends concerning Dexcom and Freestyle Libre, shedding light on user sentiments and preferences within the context of Continuous Glucose Monitoring devices. There were overall positive sentiments for both Dexcom and Freestyle Libre with some very commonly occuring negative themes. However, a majority of the data which was cateogirzed as neutral, was very subjective and also included praises and complaints regarding the products. For Dexcom, there were around 29.4% positives with 8.0% negative sentiments. While for freestyle libre the number of positives and negatives were 33.6% and 6.1% respectively. However, the polarity scores of the negative sentiments obtained about freestyle libre were higher, which indicates that they were far having a far more negative tone compared to Dexcom.

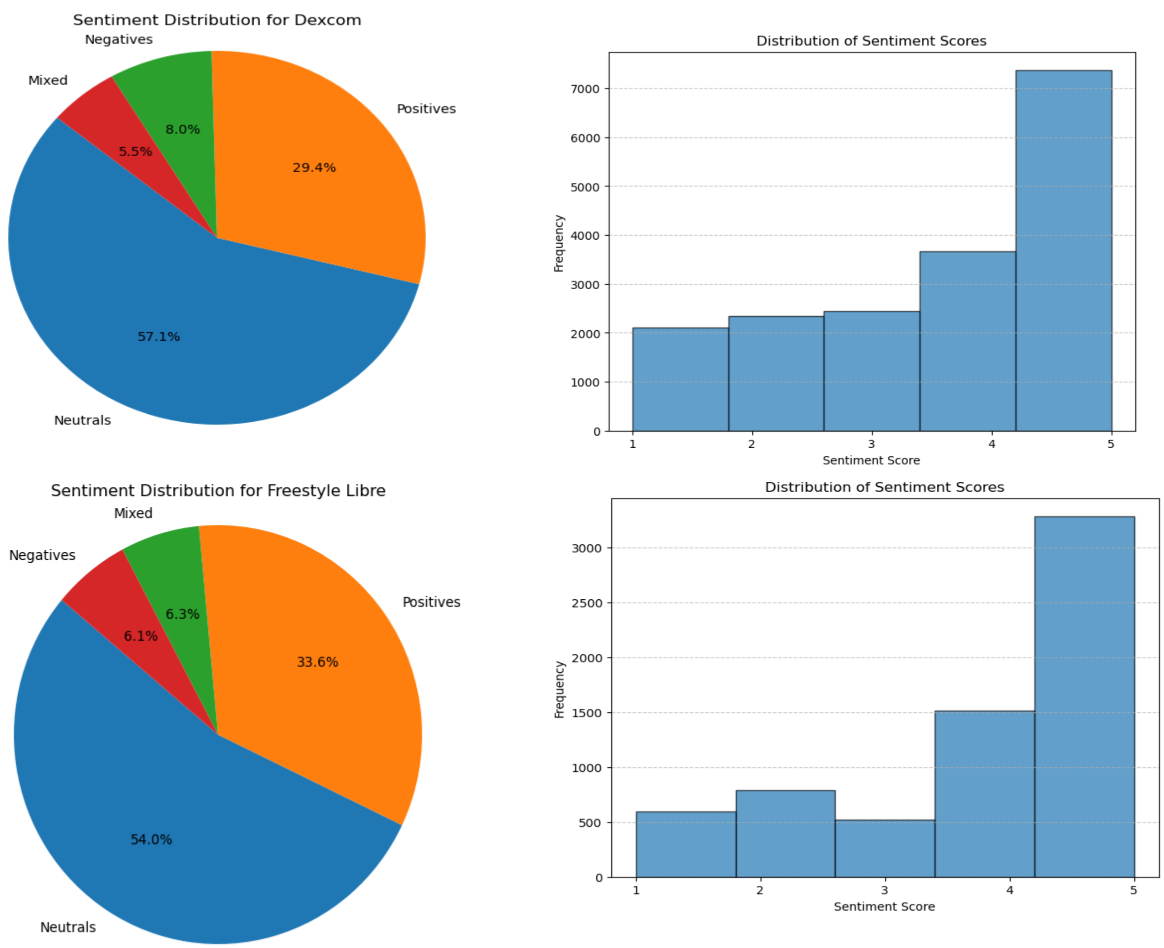

Figure 12: Product Specific Sentiments

6.1.1. Dexcom Highlights

The positive aspects of Dexcom:-

- Users highly appreciated Dexcom, particularly the Dexcom G6.
- Praises for accuracy across different segments.
- The real-time alerts for high or low glucose levels is a functionality very positively talked about.
- The data sharing functionalities which allows Dexcom to easily connect to external sources sets it apart.
- The integration with smart devices gave Dexcom an edge over competitors.

The Negative aspects of Dexcom:-

- Dexcom users encountered issues predominantly related to sensor usability.
- Affordability was a recurring theme affecting user satisfaction
- A shorter life-span for the sensors was negatively reviewed by the customers

6.1.2. Freestyle Libre Highlights

The Positive aspects about Freestyle Libre:-

- Freestyle Libre received praise for its ease of use, as customers were finding it easy in terms of usability. It has been praised over other products such as medtronic for its usability aspect.
- Longer sensor life was praised
- Although a common aspect of CGM, educed invasiveness due to elimination of finger pricks was specifically appreciated in the context of freestyle libre.
- Affordability compared to other CGM devices was another significant advantage which set it apart from the competitors.

Negative aspects and complaints about Freestyle Libre

- Users expressed concerns regarding commonly occurring sensor errors. This is an important issue because if there are sensor errors which require replacement of sensors, it can add to the cost aspect of libre. Thus, defeating the affordability aspect of the product.

- There have been numerous challenges with sensor adhesion.

- Customers expressed dissatisfaction over reduced accuracy during rapid glucose fluctuations.

- The absence of real-time alerts and the necessity for a separate reader were noted drawbacks influencing user experiences.

7. Recommendations for Product Enhancement

Along with our data analysis, Large Language Models in the form of OpenAI was also leveraged to generate recommendations. The OpenAI API was utilized to analyze the contextual information extracted along with product-specific details. The LLMs were employed to generate recommendations based on the identified classes, using the context of word clouds, bigrams, and trigrams associated with those classes. However, it's crucial to acknowledge that LLMs, despite their effectiveness, can be susceptible to issues like hallucinations, generating inaccurate information, or biased recommendations. To mitigate these concerns, a validation process was undertaken. This involved passing a set of classes derived from word clouds, bigrams, and trigrams through the LLMs to cross-reference and validate the generated recommendations. This validation approach aimed to ensure that the recommendations were aligned with the contextual understanding of the identified classes, minimizing the risk of misleading or inaccurate suggestions and enhancing the credibility of the generated recommendations. A list of classes or features that were used to generate these recommendations are:-

- Usability
- Sensor
- Cost
- Accuracy
- Alerts
- Continuous Monitoring
- Interoperability
- Customer Support

Given below is how a sample prompt was structured to ensure that the output is generated specific to the context and only relevant to the classes that have been obtained from our text analysis.

Prompt:

"Analyze the sound bites and identify the praises and complaints regarding different products namely 'Dexcom' and 'Freestyle Libre' in the following classes:

- **Usability:** Extract insights related to the ease of use, interface, and user-friendliness of the products.
- **Sensor:** Gather feedback concerning the sensor's performance, durability, and reliability.
- **Cost:** Analyze opinions regarding the pricing, value for money, and affordability of the products.
- **Accuracy:** Extract sentiments and comments regarding the accuracy and precision of the devices in monitoring blood glucose levels.
- **Alerts:** Gather information on the effectiveness and reliability of alerts, including high and low blood sugar notifications.
- **Continuous Monitoring:** Identify opinions and experiences related to continuous monitoring features.
- **Interoperability:** Extract insights on the compatibility and integration of the devices with other systems or apps.
- **Customer Support:** Analyze feedback about customer service experiences, including support quality and responsiveness.

Generate insights on the praises and complaints for each class based on the provided sound bites."

Figure 13: Sample prompt used for LLMs

7.1. Recommendations for Freestyle libre

In order to address the commonly occurring issues and complaints about customers, the following product aspect need to be worked on:-

- **Connectivity & Sensor Reliability:** Address sensor connectivity issues reported by some users to improve overall reliability. Ensuring the sensors are reachable and offer continuous and uninterrupted monitoring is crucial.

- **App and Watch Connectivity:** Enhance the Libre app's connectivity with smartwatches and phones for more reliable and real-time data updates, especially on the watch app.

- **Accuracy & Alarms:** Enhance the accuracy of readings and the reliability of alarms. Users have reported issues with sensor readings and alarms, requiring frequent checks and sometimes causing false low readings.

7.2. Recommendations for Dexcom

- Dexcom can be expensive and may not be affordable for everyone especially without insurance coverage. This can be better addressed by partnering with insurance providers or offering flexible payment options so more customers can get access to Dexcom.

- Battery Considerations: Exploring rechargeable or replaceable battery options for transmitters could reduce waste and improve sustainability.

- Increase lifespan of sensors Since app connectivity is important and sets Dexcom apart, complaints regarding disconnections need to be addressed.

Conclusion

The analysis provided insights into user experiences, preferences, and emerging trends uncovering valuable information regarding Dexcom and Freestyle Libre. It also shed light on their positive attributes, common complaints, and user preferences within the domain of diabetes care. The incorporation of data science approaches into product development exemplifies the transformative power of data-driven insights in shaping product strategies. By leveraging these techniques such as sentiment analysis, machine learning models, and social media analytics, we were able to acquire an essential perspective on user preferences, and also identify some emerging trends. These insights serve as a guide for more informed decision making in product management.

Future Research and Development

Some recommendations for future steps that can be taken to enhance this research is as follows:-

- Fine-Tuning Sentiment Analysis Models: Further refinement of sentiment analysis models using techniques such as deep learning algorithms to improve accuracy and granularity in understanding user sentiments regarding CGM devices. A multi layer perceptron model has been utilized by some studies in natural language processing which can generate good results.

- Refining machine learning models: The models used in our analysis can be further improved by addressing imbalanced data through oversampling or undersampling methods, and employing regularization techniques. As per the scope of this analysis only accuracy was used as a measure however, other metrics such as f-score, precision and recall can be utilized to better understand the performance.

- Utilize the temporal topic evolution in alignment with product timeline; after releasing new product or features as it can help unearth how these are perceived by different customers.

References

[1] Rodbard, David. "Continuous glucose monitoring: a review of successes, challenges, and opportunities." *Diabetes technology & therapeutics* 18, no. S2 (2016): S2-3.

[2] Boscari, Federico, et al. "Head-to-head comparison of the accuracy of Abbott FreeStyle Libre and Dexcom G5 mobile." Nutrition, Metabolism and Cardiovascular Diseases 28.4 (2018): 425-427.

[3] Klonoff, David C., David Ahn, and Andjela Drincic. "Continuous glucose monitoring: a review of the technology and clinical use." *Diabetes Research and Clinical Practice* 133 (2017): 178-192.

[4] OpenAI. "OpenAI API: Language Models." https://openai.com/api/.

Appendix

- Github: https://github.com/ahmadfaraz2024/GCM_Text_Analysis
- NB Viewer: https://nbviewer.org/github/ahmadfaraz2024/GCM_Text_Analysis/blob/main/GCM.ipynb#topic=0&lambda=1&term=