Background/questions

Our team analysed historical appointment data from NHS England for General Practice Surgeries. As the NHS seeks to accommodate its growing population, it must allocate resources effectively. Understanding utilisation trends within its network is crucial for budget planning. For that, I examined four key aspects.

1. Utilisation Trends:
    a. What are the overall trends in utilisation of NHS services over time?
    b. How do utilisation trends vary across different components of the NHS network?
    c. Are there any seasonal or temporal patterns in utilisation?
2. Capacity Assessment:
    a. How does current utilisation compare to the available capacity within the NHS network?
    b. Are there specific areas within the NHS network experiencing overutilisation or underutilisation?
3. Missed Appointments:
    a. What is the rate of missed appointments across different NHS services?
4. External Data Integration:
    a. Is there a potential value of incorporating external data sources such as Twitter?

Analytic approach:

I used Python to explore the data spread on three files obtained from integrated care board (ICB), and a Twitter data related to healthcare in the UK.

Our first approach was to explore the dataframes structure and limitations.

- The location data was recorded at various levels. Employing 'l*en'* and '*unique.()'* functions, I determined that there are 7 regions, 42 ICB locations and 106 sublocation. There were discrepancies in granularity across files, with the ICB serving as a potential primary key.

- I also noticed that there are 5 service settings, 3 context types, 18 national categories, and 3 appointment statuses. For a more detailed view and explanation of the file contents, please refer to Appendix Figure 1.

- Using the *datetime, min()* and *max()* function, I determined the earliest and latest dates present in each file, revealing that they cover distinct time periods.
    - Appointment Regional (ar): JAN-2020 to JUN-2022
    - National Category (nc): 01-AUG-2021 to 30-JUN-2022
    - Actual Duration (ad): 01-DEC-2021 to 30-JUN-2022

- The 'ad' file records dates at the daily level, whereas the other files have monthly data. By utilizing the *datetime* function, I extracted the month and year, aligning the granularity with the other files.

- To calculate the total appointments per month, I grouped appointments by month using the *.groupby()* function and then used *.sum()*. For calculating the record count, I followed a similar approach, but employing *.count()*.

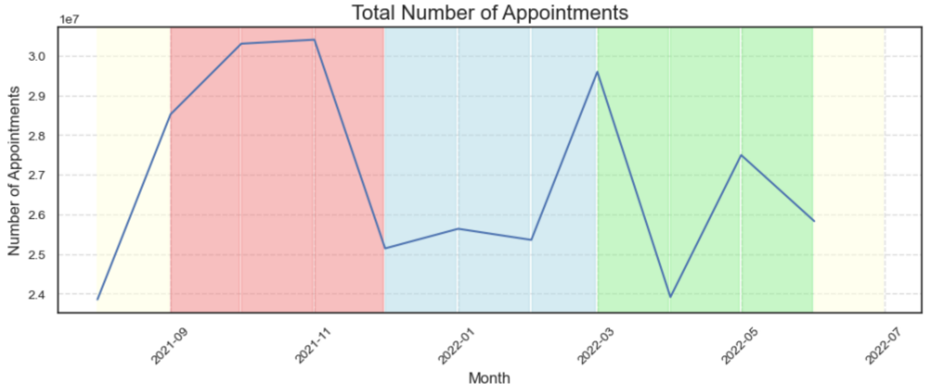
- "ar" and "nc" have equal total appointments but differ in counts due to different recording methods. "ad" displays fewer appointments due to incomplete recording (Appendix-table1). “ad” is not reliable as the recording of appointment duration varies across different practices. Therefore, it won’t be part of my main analysis. Further details can be found in Appendix-Figure2.

- The analysis covers the period from August 2021 to June 2022.

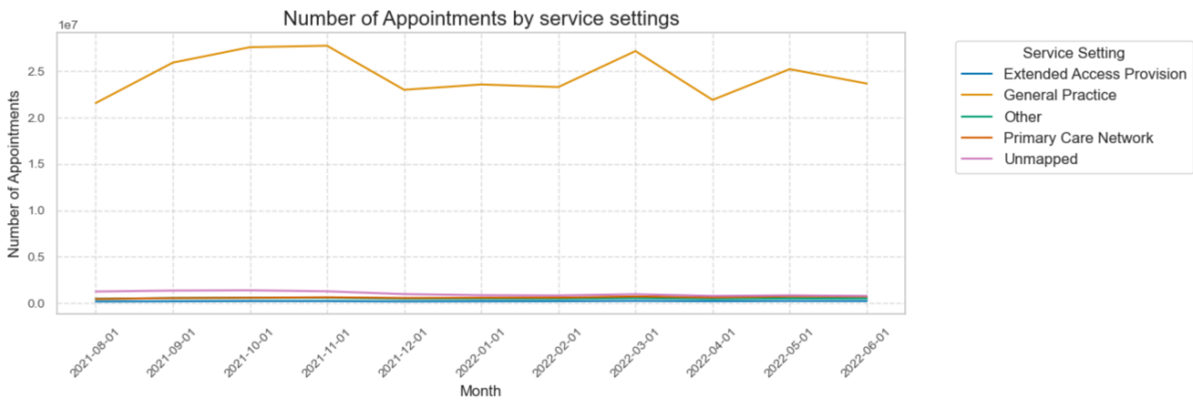
Patterns and trends:

Utilisation Trends:

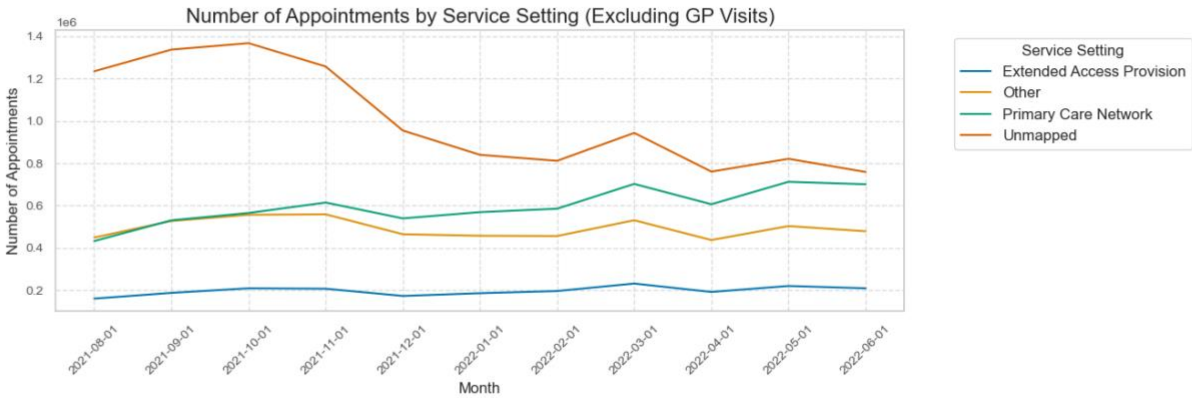
- To provide an overview of appointment trends, Total appointments per month was plotted and seasons highlighted by shading the background. Surprisingly, there was a decrease in appointments observed between November and January.



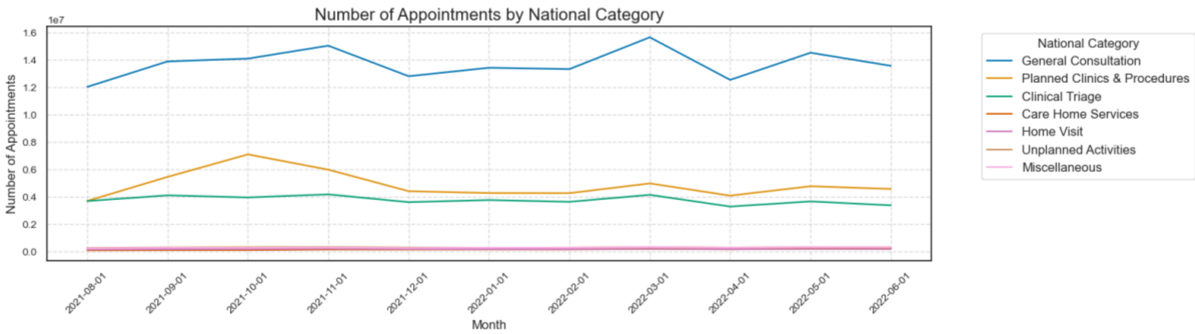
- For increased granularity, I employed a hue defined by 'service-setting’, revealed that General-Practice (GP) was more utilized than the others.



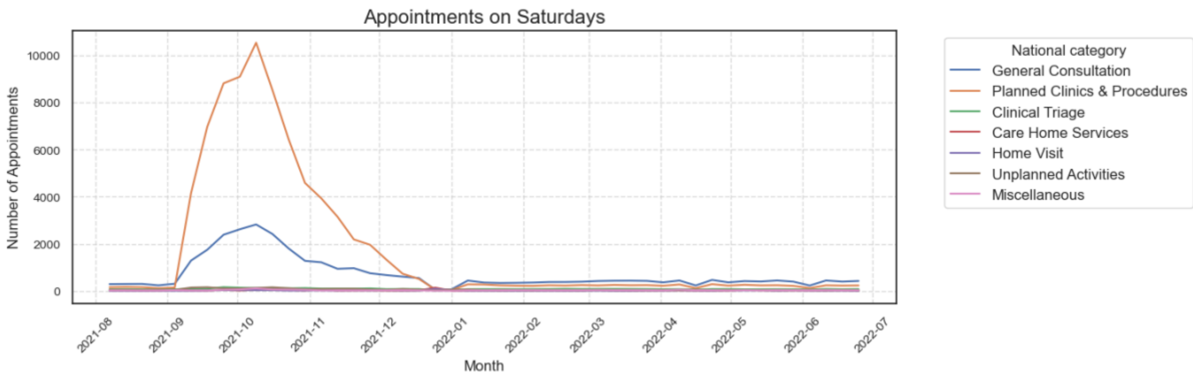
- To allow better readability, GP data was filtered out and the trend reveals a steady increase in PCN and a decline in unmapped-appointments. This prompts the question of whether PCN numbers would be higher with proper mapping. Improved mapping may provide more accurate PCN figures.



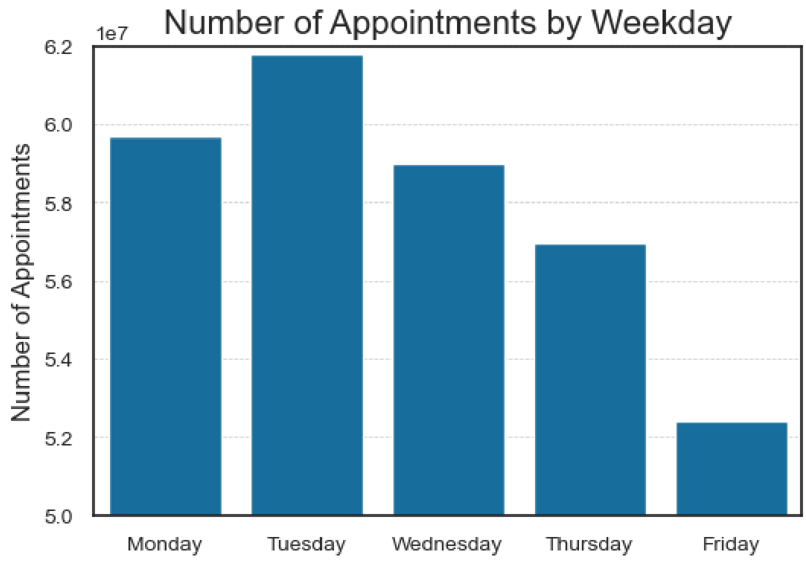
- Utilizing hue in national category analysis resulted in a cluttered chart due to the presence of 18 categories(Appendix-Figure3-5). To improve clarity, I grouped similar categories. “General-Consultation” was the most frequent category, an increase was observed in “Planned-Clinics-&-Procedures” in October.



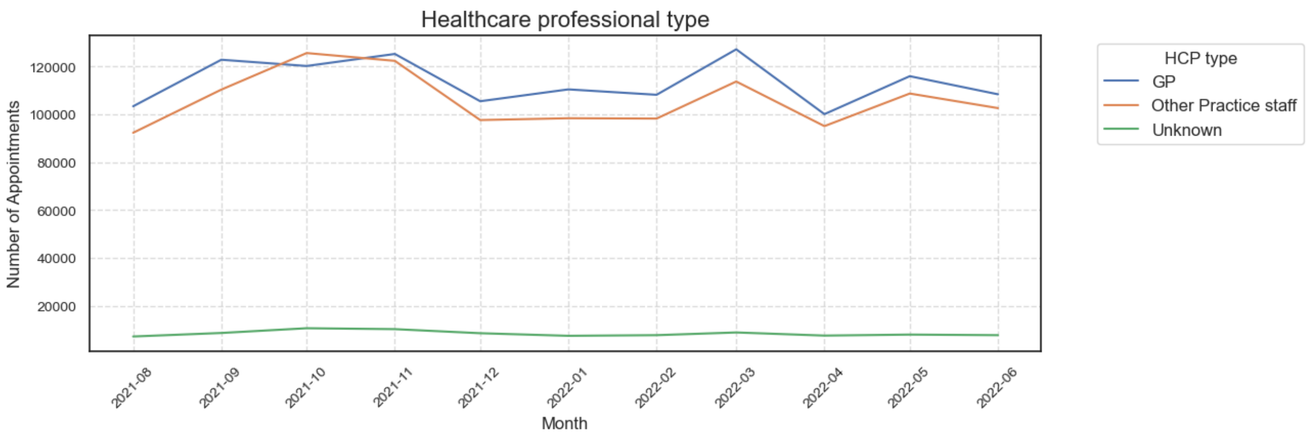
- With daily granularity and *dt.dayofweek,* appointments were analysed on each weekdays and became clear that the rise in “Planned-Clinics-&-Procedures” was due to Saturday clinics. It happened nationwide.(Appendix-Figure6).



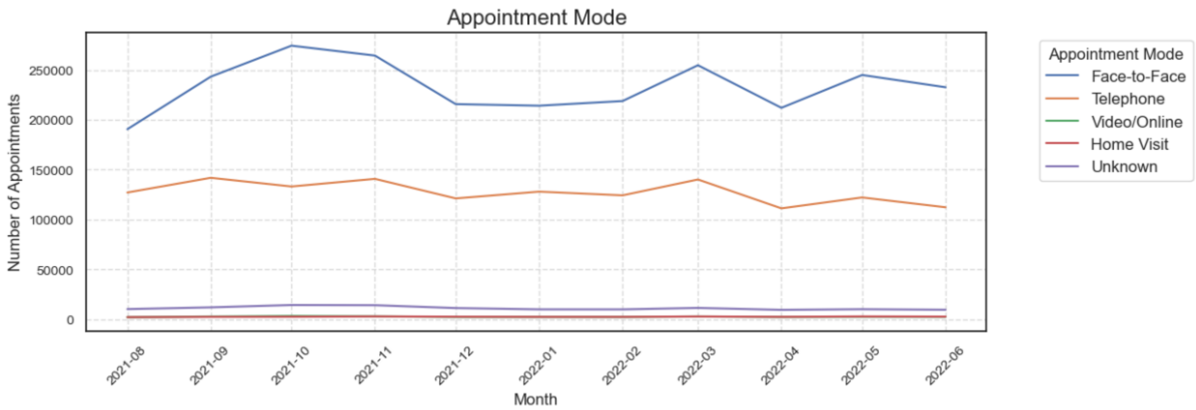
- Utilizing the *dt.weekday* function, I grouped appointments by weekday and summed their counts, visualizing the findings on a bar plot. Friday experienced nearly 10 million fewer appointments compared to Tuesday.



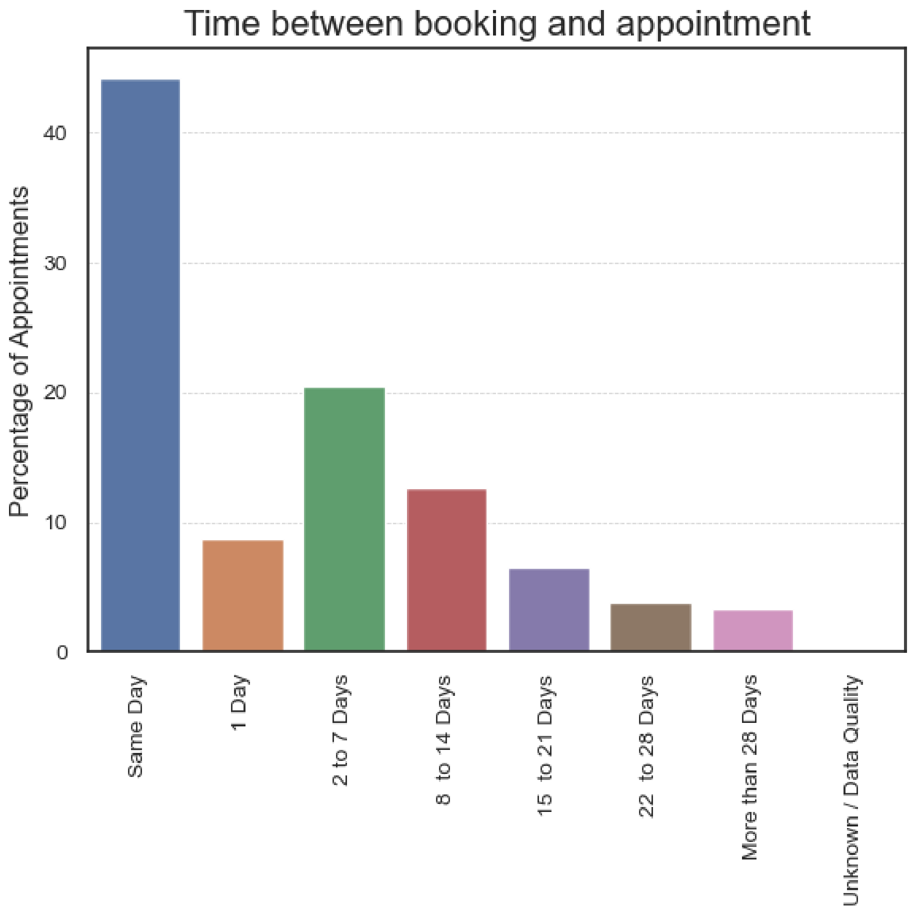
- Regarding healthcare professionals (HCP), most appointments involve GPs throughout the year, except for October when Other-Practice-Staff see an increase. Other-Practice-Staff comprises range of 12 professional types, including nurses. It's crucial to discern between different professionals for improved planning.



- Face-to-face appointments constitute the majority (61%), with telephone appointments representing a significant portion (37.87%). Notably, face-to-face appointments see an increase during the busiest months from September to December, while telephone appointments remain relatively stable. This suggests that during periods of increased demand, patients tend to prefer or require face-to-face appointments.

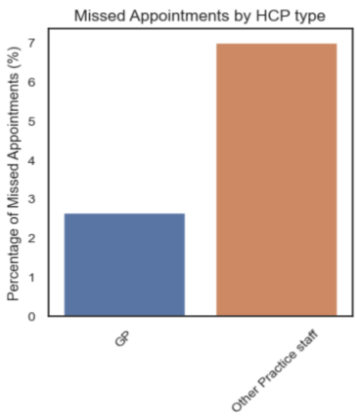


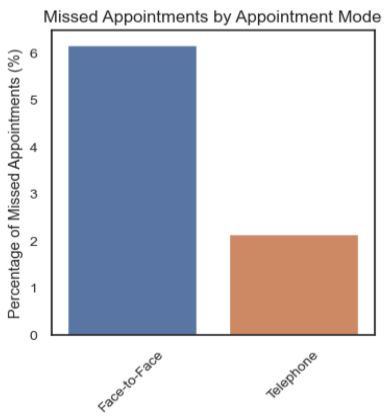
- Most appointments were booked for the same day (46%), suggesting that a significant portion of patients prefer or require short notice appointments. However, the next most common timeframe is 2-7 days, rather than 1 day. This might reflect the inability to book an appointment for the next day.

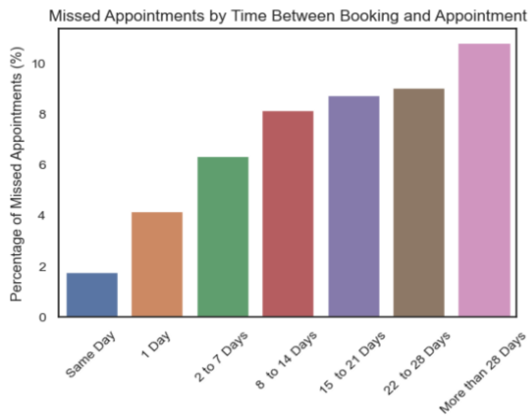


Missed Appointments:

- Most appointments were attended, with 4.6% recorded as missed, totalling 13,318,384 missed appointments during the analysed period. Further analysis indicates that appointments with GPs have lower miss rates compared to those with Other-Practice-Staff. Additionally, face-to-face appointments are more prone to being missed than telephone appointments, and longer lead times between booking and appointments increase the likelihood of a missed appointment.

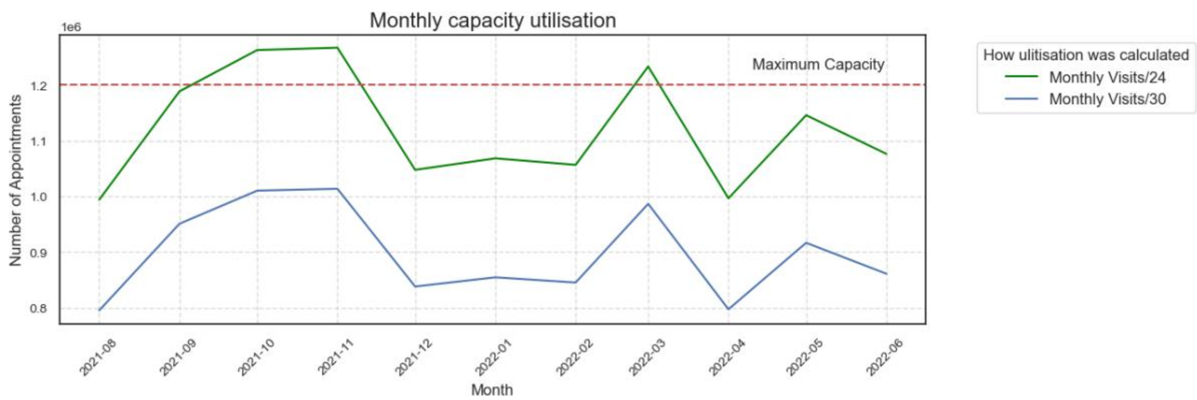






Capacity Assessment:

- NHS sets daily capacity at 1,200,000 appointments. Monthly usage calculated by dividing total appointments by 30 days or by 24 hours (as most occur Monday to Friday). Utilization peaks at 20% of capacity when divided by 30 but exceeds by 10% when divided by 24. Limitations include lack of staff and infrastructure data. Doesn't consider regional demographics or healthcare needs.



- Filtering Twitter data for favourited and retweets reveals a transition from marketing-focused tweets to more meaningful discussions. Yet, strict filtration, especially beyond two retweets, may overlook crucial NHS-related hashtags like "digitalhealth" and "vaccine." This highlights the need for NHS to bolster its promotional efforts. Incorporating insights from retweets alongside comprehensive hashtag analysis can provide valuable feedback to stakeholders, enriching project outcomes.(Appendix-Figure9-13).

Recommendations:

1. Capacity Assessment:
    a. Gathering data on staff, infrastructure, regional demographics, and healthcare needs is crucial for comprehensive capacity assessment and planning.
2. Utilisation Trends:
    a. Autumn's Saturday clinics throughout the year.
    b. Increase appointments towards the end of the week.
    c. Separate “Nurse” data from “Other-Practice-Staff”.
    d. Increase Face-to-Face capacity during peak months.
    e. Enable next-day booking.
3. Missed Appointments:
    a. Targeted reminders (Other Staff or long-term booking)
    b. Optimize appointment scheduling to reduce wait times.
    c. Tailor patient education to specific healthcare contexts
4. Data collection:
    a. Assign unique-ID to appointments for merging files and enabling the extraction of insights such as missed appointments by weekday and HCP.
    b. Improve service setting records.
    c. Standardise surgeries records of actual appointments duration.

Further areas to explore:

- Map regions across all files, and do analysis on specific locations.

Appendix:

Fig 1: Structure of the files.

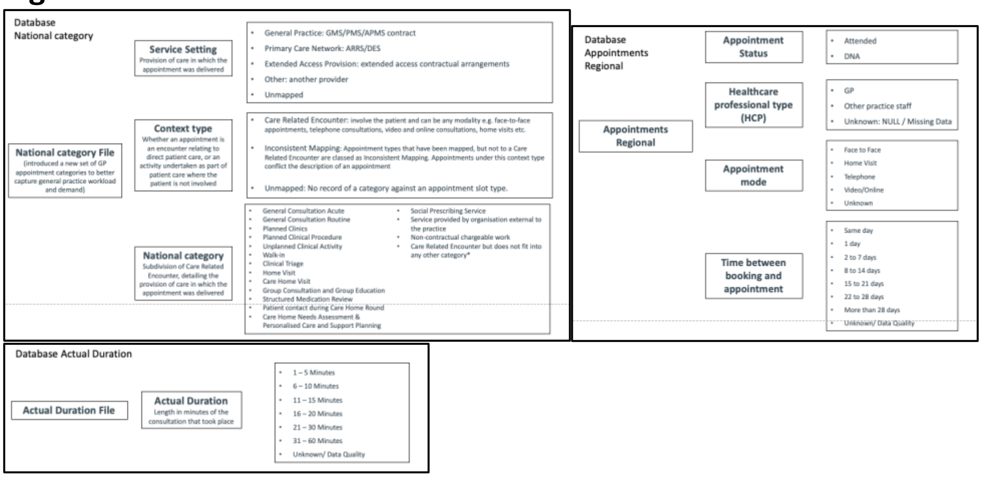


Table 1. To facilitate comparing the total appointments and records by month across the three files, each result was stored as a dataframe and then combined using the .concat() function.

		sum_of_appointments_nc	sum_of_appointments_ar	sum_of_appointments_ad
2021	11	30405070.0	30405070	NaN
	10	30303834.0	30303834	NaN
2022	3	29595038.0	29595038	27170002.0
2021	9	28522501.0	28522501	NaN
2022	5	27495508.0	27495508	25343941.0
	6	25828078.0	25828078	23715317.0
	1	25635474.0	25635474	23597196.0
	2	25355260.0	25355260	23351939.0
2021	12	25140776.0	25140776	22853483.0
2022	4	23913060.0	23913060	21948814.0

		count_of_appointments_nc	count_of_appointments_ar	count_of_appointments_ad
2021	8	69999.0	19786	NaN
	9	74922.0	20441	NaN
	10	74078.0	20562	NaN
	11	77652.0	20766	NaN
	12	72651.0	20393	19507.0
2022	1	71896.0	20225	19643.0
	2	71769.0	20133	18974.0
	3	82822.0	20532	21236.0
	4	70012.0	20073	19078.0
	5	77425.0	20276	20128.0

Fig 2. Most appointments, including during peak periods, last up to 10 minutes, highlighting the importance of considering appointment duration when scheduling. However, it has several limitations, such as almost one-quarter of appointments having unknown or poor data quality. Additionally, it cannot be integrated with other datasets for further exploration, such as examining healthcare professional types and appointment modes.

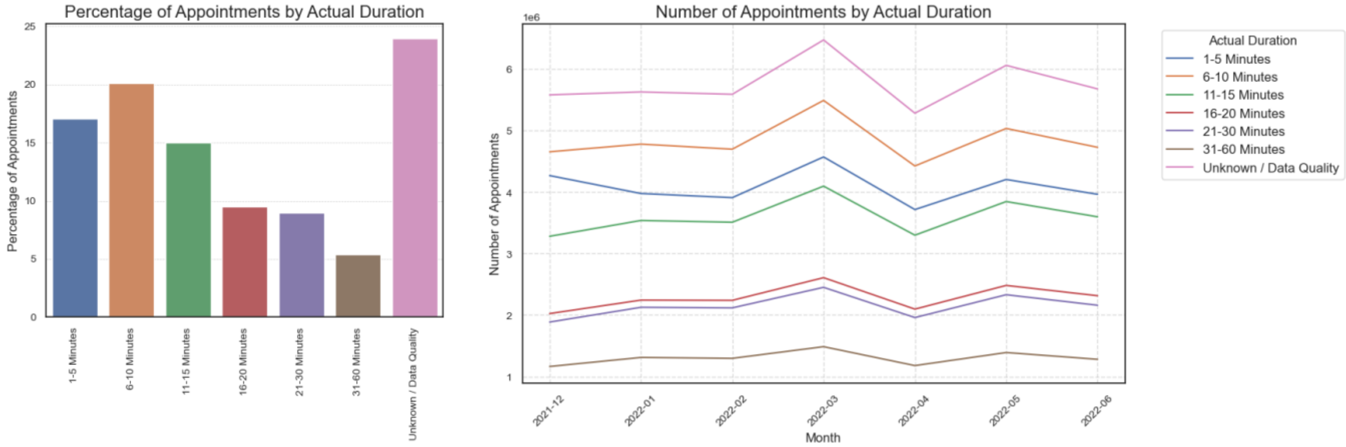


Fig 3: National category chart with all categories. There is an increase in “Planed Clinics” and “Planned Clinical” procedures.

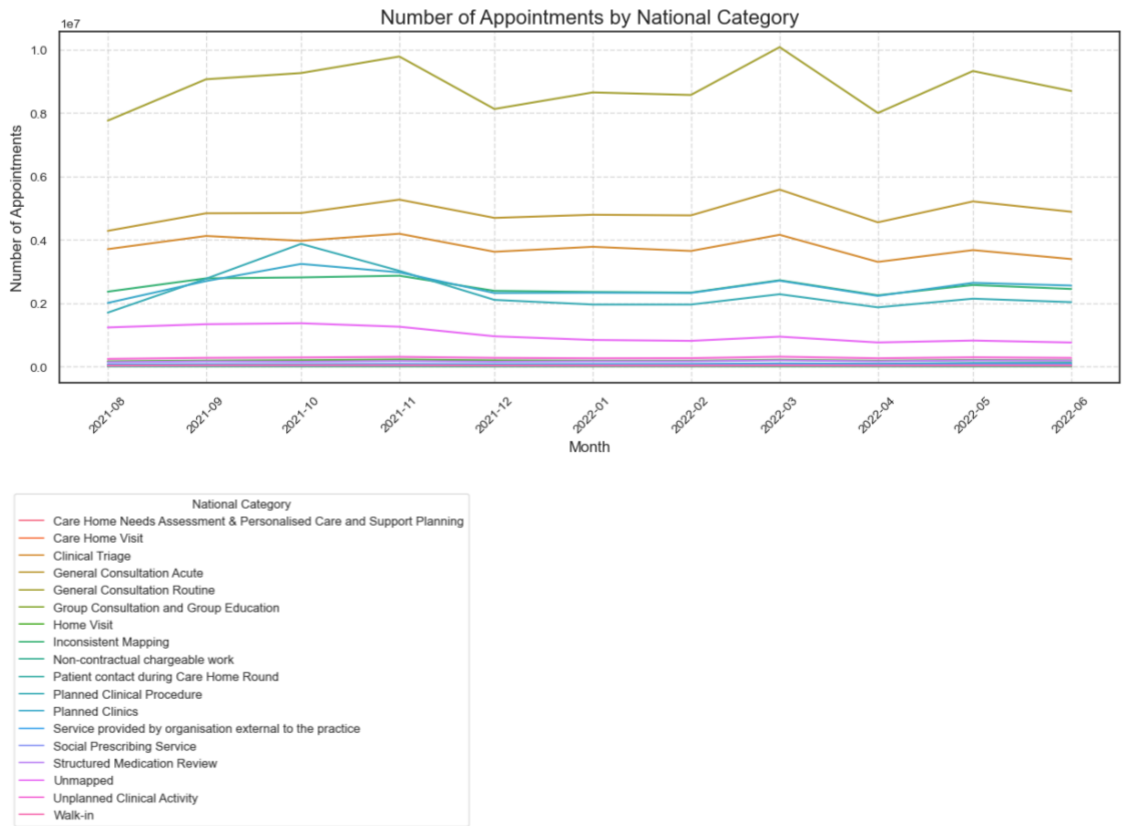


Figure 4: To group similar categories, a bar chart was plotted to visualize the sum of appointments. A log scale was employed to highlight categories with fewer appointments."

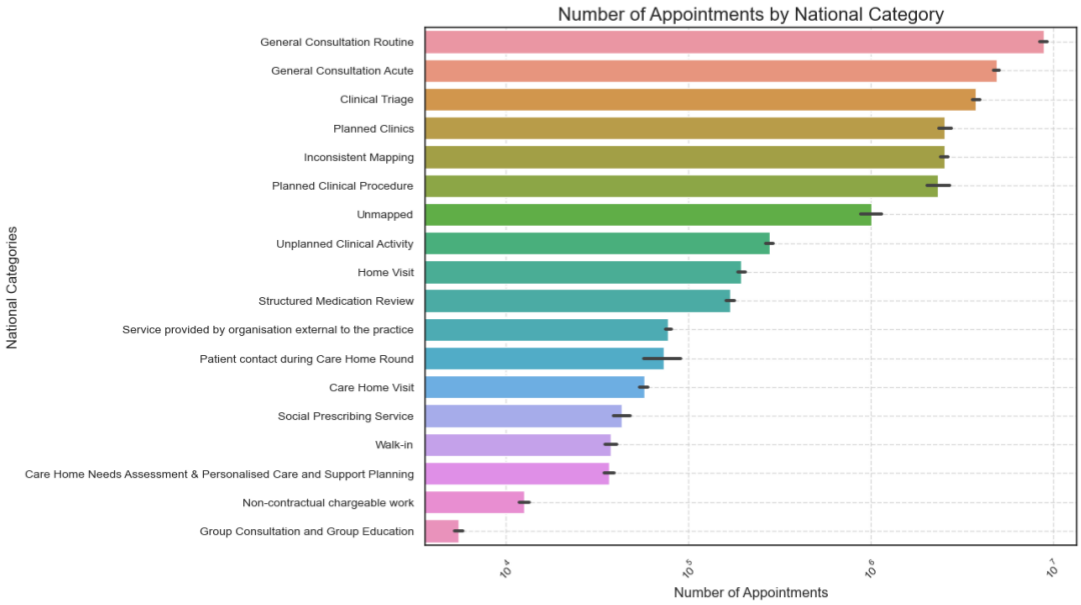


Fig 5. Combined categories:

Original	Combined
General Consultation Acute	General Consultation
General Consultation Routine	General Consultation
Planned Clinics	Planned Clinics & Procedures
Planned Clinical Procedure	Planned Clinics & Procedures
Patient contact during Care Home Round	Care Home Services
Care Home Visit	Care Home Services
Care Home Needs Assessment & Personalised Care and Support Planning	Care Home Services
Unplanned Clinical Activity	Unplanned Activities
Walk-in	Unplanned Activities
Structured Medication Review	Miscellaneous
Social Prescribing Service	Miscellaneous
Non-contractual chargeable work	Miscellaneous
Group Consultation and Group Education	Miscellaneous
Service provided by organisation external to the practice	Miscellaneous

Fig 6. In order to identify where the Saturday clinics happened, I aggregated on "sub_icb_location_name" and sum the "count_of_appointments"

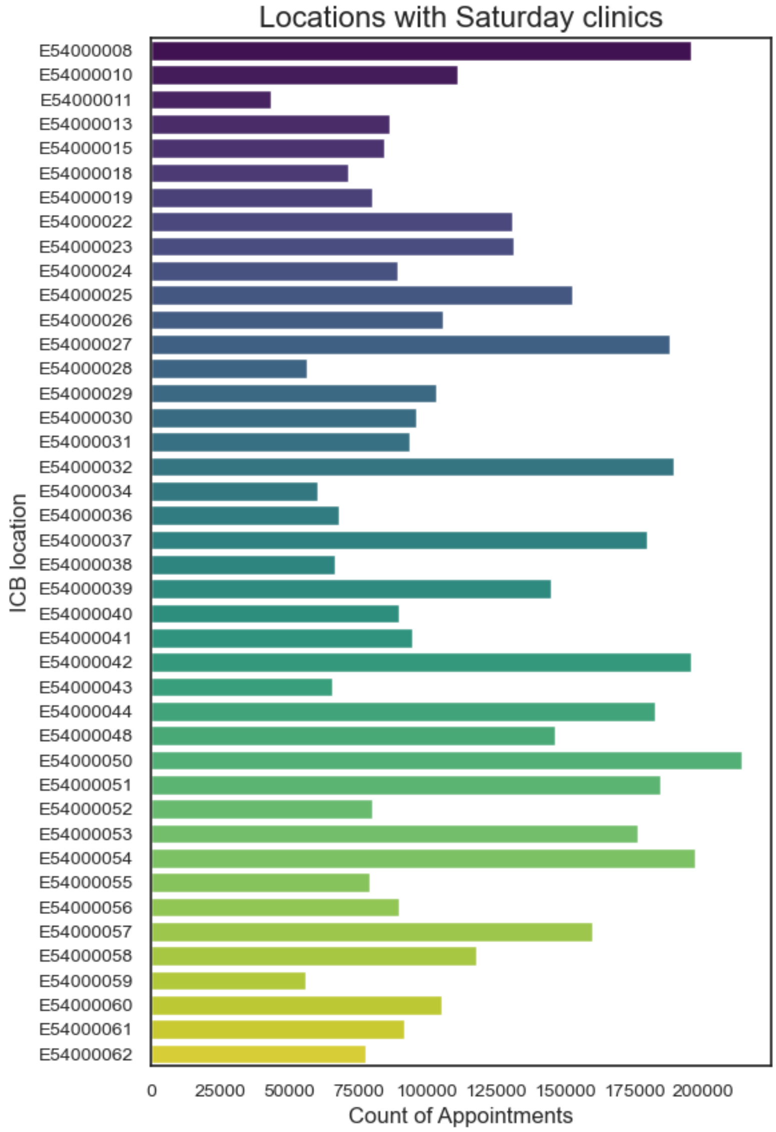


Fig 7. Employing daily granularity, I observed a consistent pattern revealing a peak in appointments at the beginning of the week, followed by a gradual decline throughout the week, culminating in a drop over the weekend.

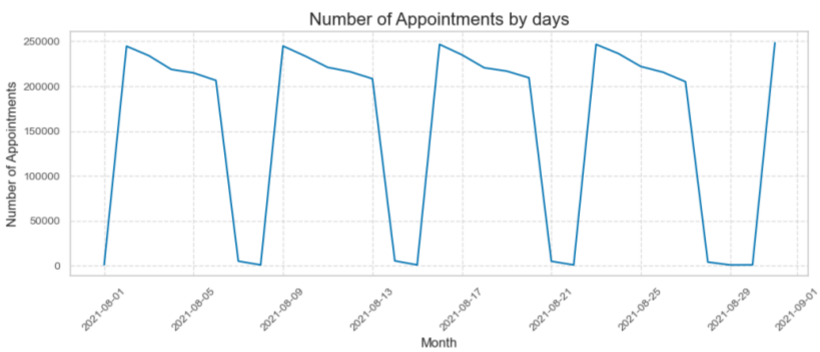


Fig 8. Utilizing hue defined by 'Context Type' does not yield valuable insights, since there are no additional categories beyond 'Care related encounter.'

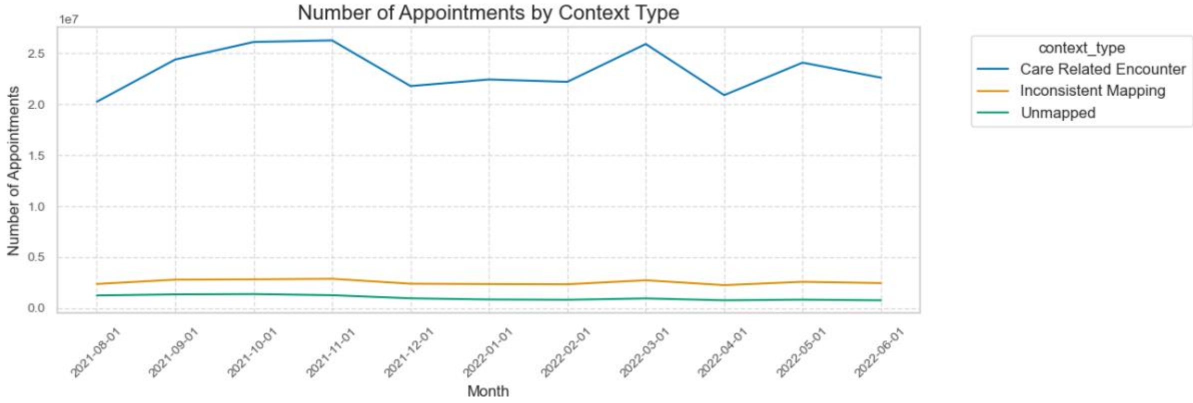


Fig 9. The top 20 most frequently used hashtags, appearing at least 10 times after filtering out #healthcare (the hashtag upon which this database is built) reveals a broader conversation on Twitter. Notably, hashtags such as #strategy, #pharmaceutical, #marketing, and #jobs emerge, indicating a diverse range of topics being discussed. While these may not be directly related to NHS, understanding the broader context is crucial for staying informed about relevant discussions on Twitter.

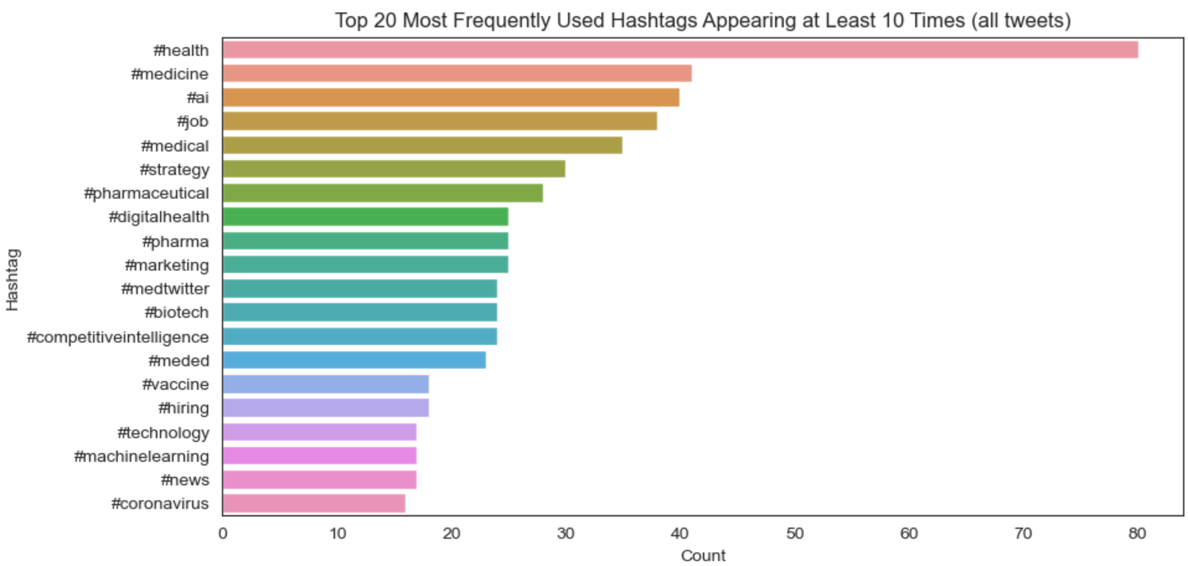


Fig 10. Filtering for tweets with more than one retweet or favourite provides clearer visibility of important hashtags for the NHS, such as #digitalhealth, #vaccine, and #science, among the top trending hashtags appearing at least 10 times. This refined approach ensures a focus on discussions that have garnered more engagement, highlighting key topics relevant to the NHS mission and objective.

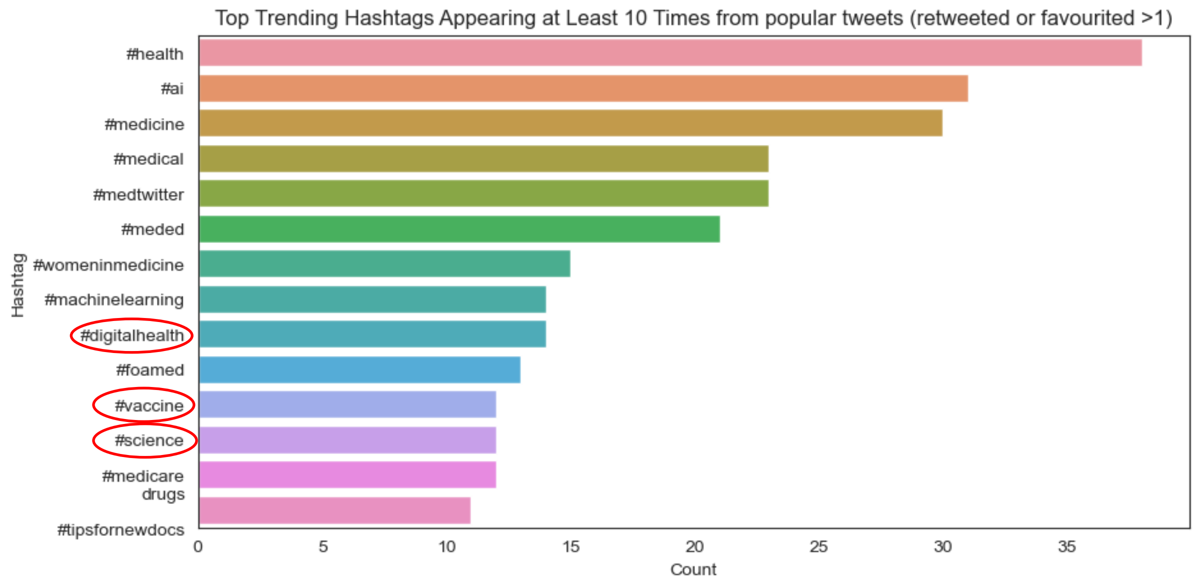


Fig 11. Filtering for tweets with more than two retweets or favourites results in a shift where previously important hashtags highlighted above no longer appear among the top trending hashtags appearing at least 10 times. This suggests a potential change in focus or engagement patterns, emphasizing the dynamic nature of Twitter discussions. It underscores the importance of flexible analysis approaches to capture evolving trends effectively and highlights the potential impact of influential individuals in promoting NHS hashtags.

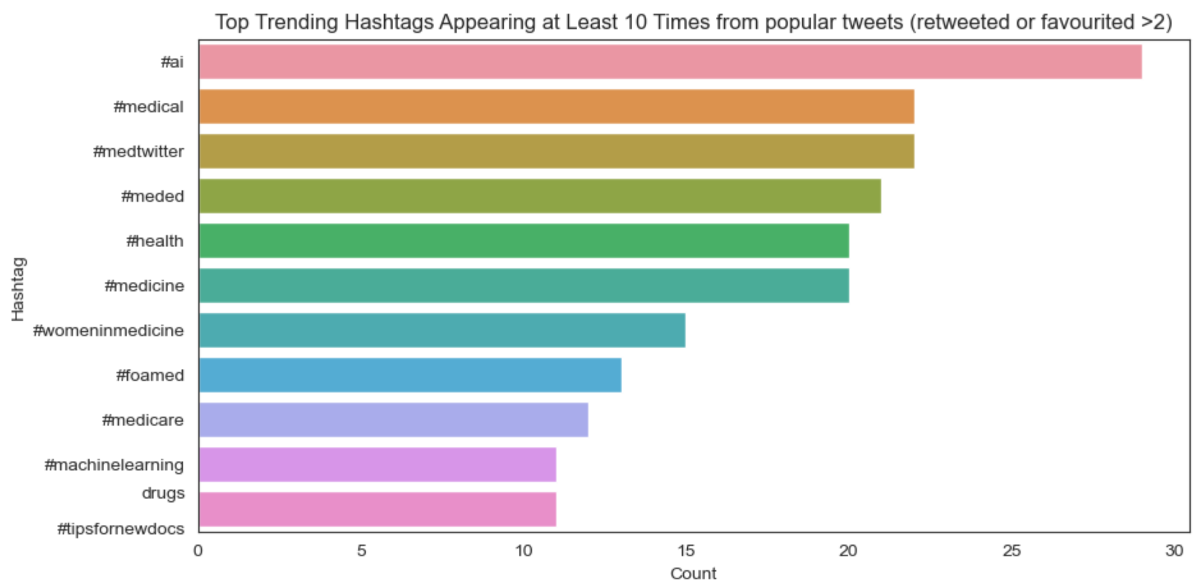


Fig 12. Word clouds are a popular and visual way to analyse social media data. In a word cloud, the size of each word corresponds to its frequency of appearance in the text data. This visualization method allows for quick identification of the most common words or themes within the dataset, providing insights into prevalent topics, sentiments, or trends in social media discussions. I did this analysis using the package *WordCloud*.

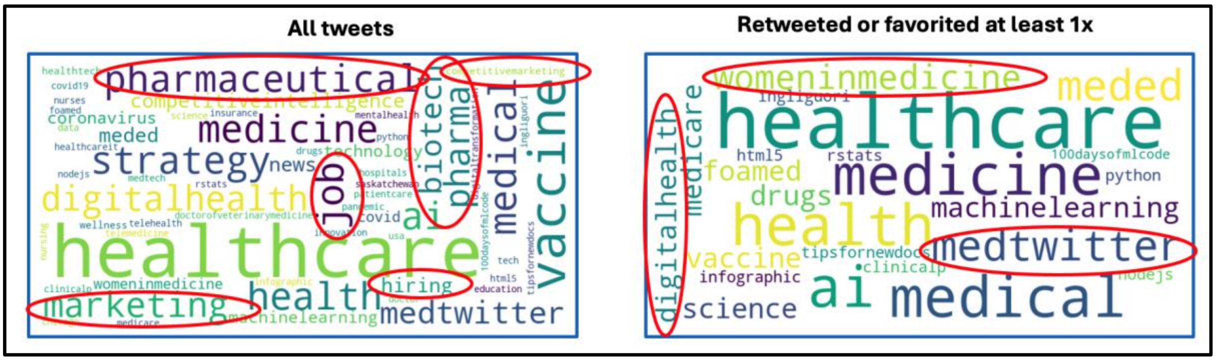


Fig 13. Sentiment analysis is a crucial method for examining social media data, offering insights into the sentiment expressed in the text, categorizing it as positive, negative, or neutral. Additionally, sentiment analysis can provide insights into the subjectivity of the text, distinguishing between objective and subjective content.
In our dataset, tweets with healthcare hashtags predominantly exhibit neutrality and objectivity. During analysis, I compared two sentiment analysis packages: *Vader* and *TextBlob.* While both yielded similar polarity scores, *TextBlob* provided subjective scores which were absent in Vader's results. Therefore, I present the *TextBlob* findings for a more comprehensive analysis.