NHS Appointment Capacity and Utilization Analysis – Technical Report

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Contents

1. Background context

The NHS tasked me to evaluate their staffing capacity, and resource utilization across the period January 2020 to July 2022, a period heavily influenced by the coronavirus pandemic. This report will be used to understand trends and recommend how they should allocate their budget efficiently to reduce missed appointments. This report is for **NHS's data team**.

This report will study the following 2 questions:

- ***"Has there been adequate staff and capacity in the networks?"***
- ***"What was the actual utilisation of resources?"***

A **problem-solving framework** can be found in a Five Why's Diagram *(Appendix 1a)* and a Fishbone diagram *(Appendix 1b)*

Business objective: Improve efficiency in GP resources and reduce missed appointments.

2. Analytical approach

- As explicitly stated in the metadata, the data has already been **cleaned**. Therefore, **data cleaning** wasn't mandatory, nevertheless python was used to manipulate any unwanted data during analysis.
- The metadata also states, the data was not originally designed to be analyzed due to lack of national standard for data entry. This resulted in extensive data quality issues and limited our ability in finding insights, so caution is advised in interpreting this analysis and consequently there was no **outlier** treatment.
- Only the 'ar' dataset contained **duplicates** which accounts for only 3.6% of the data. I decided not to remove duplicates as this value is too low to impede our analysis. Also, due to poor data quality standards related to misalignment between healthcare systems, it is difficult to ascertain whether they are genuine duplicates.
- Only the 'tweets' dataset contained **null values**. I decided to leave the data untouched to see if twitter analysis had any general value to solving our problem.

- For certain aspects of my analysis, I mapped the 'time_between_book_and_appointment' column from categorical to numerical values i.e. 'average wait time'. This was used to understand correlation and average wait time.

time_between_book_and_appointment	**average wait time (days)**
same day	0
1 day	1
2 to 7 days	4.5
8 to 14 days	11
15 to 21 days	18
22 to 28 days	25
more than 28 days	32
Unknown / Data Quality	***excluded as only makes up 0.05% of total appointments***

Assumption - 32 days as an average wait time for the 'more than 28 days' category to ensure interval consistency and a fair representation of the distribution of data.

Limitation - Inability to join all three appointment datasets due to how the data was aggregated. However, given the different timeframes, joining the data would only be productive for a smaller timeframe that all three datasets cover. Ultimately joining the data was not required to address the questions.

- I filtered out 'unknown' values for 'appointment mode', 'wait time', 'hcp type' and 'appointment status' for certain aspects in my analysis as they don't provide any technical connotation. I also joined the 'ar' dataset with a separate 'icb & region' dataset for regional specific insights. Majority of the insights are based on the 'ar' and 'nc' datasets as they cover the largest data period.

Note: I also conducted a Twitter analysis but decided against exploring it further as it was not directly applicable to my area of investigation. A brief analysis can be seen in the appendix (*Appendix 9)*

<u>**Jupyter Notebook**</u>

Firstly, we prepare our workstation

- Import necessary libraries. Pandas for data wrangling, Numpy for numerical calculations, Matplotlib and Seaborn for data visualization (*Appendix 2a*)
- Setting the style and color palette of visualizations to ensure accessibility.
- The writing of python code was aimed to comply with PEP 8 principles and be pythonic for effective interpretation.
- Import and sense check data (*Appendix 2b*)

<u>**Data Wrangling**</u>

The 4 data files were imported into Jupyter Notebook due to its extensive python libraries and automation capabilities. Pandas was used for data wrangling to allow me to filter and reshape the data to my intended requirement. Using functions like group by, map, loc allowed me to achieve this.

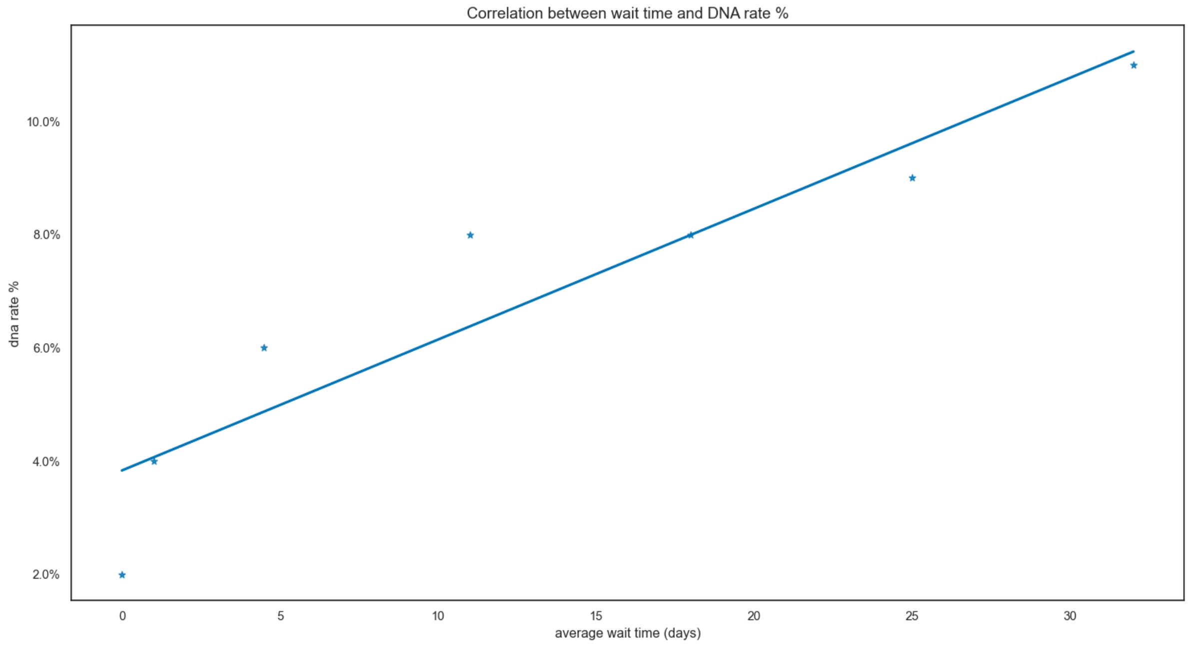
<u>**Utilization**</u>

I was given a figure of 1.2 million appointments as the NHS maximum daily capacity. Thus, to calculate the monthly utilization I used the below calculation, assuming 30 days in any given month.

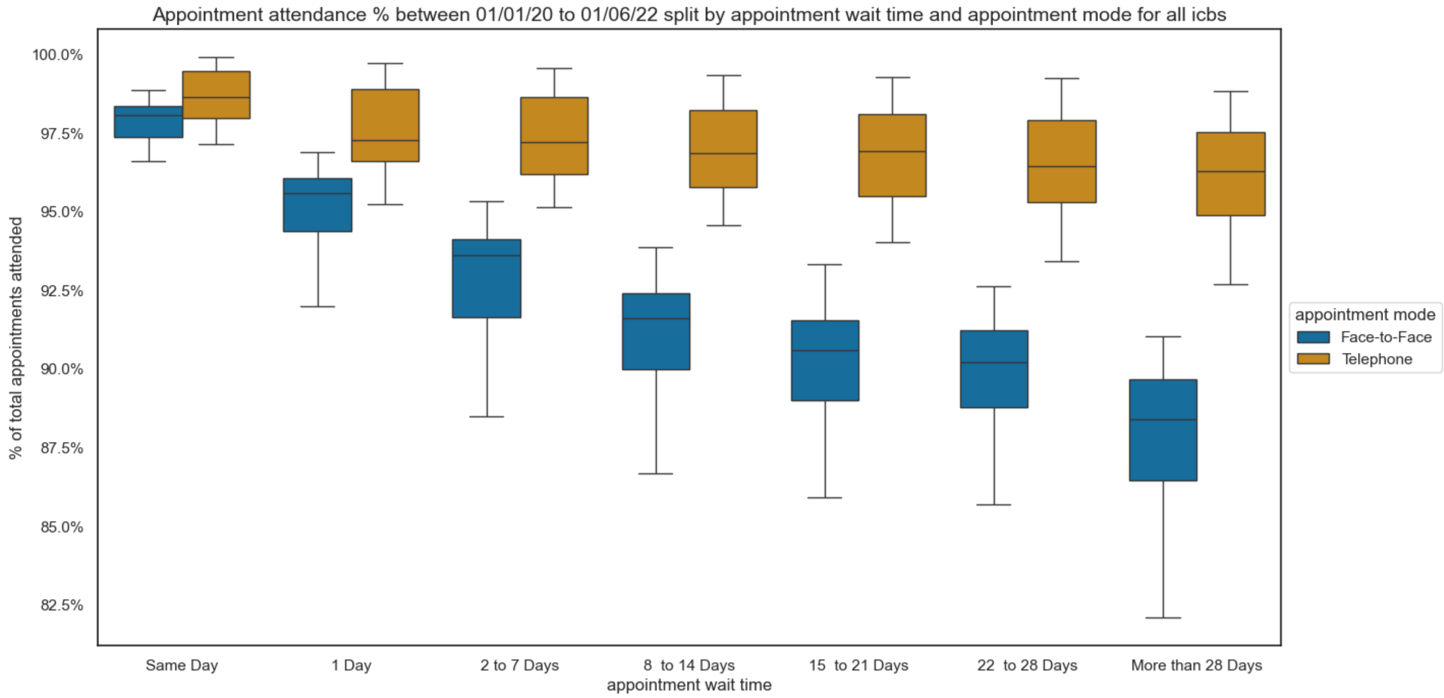
$$\text{Monthly utilization } \% = \left(\frac{\text{Total monthly appointments}}{1.2M \times 30}\right) \times 100$$

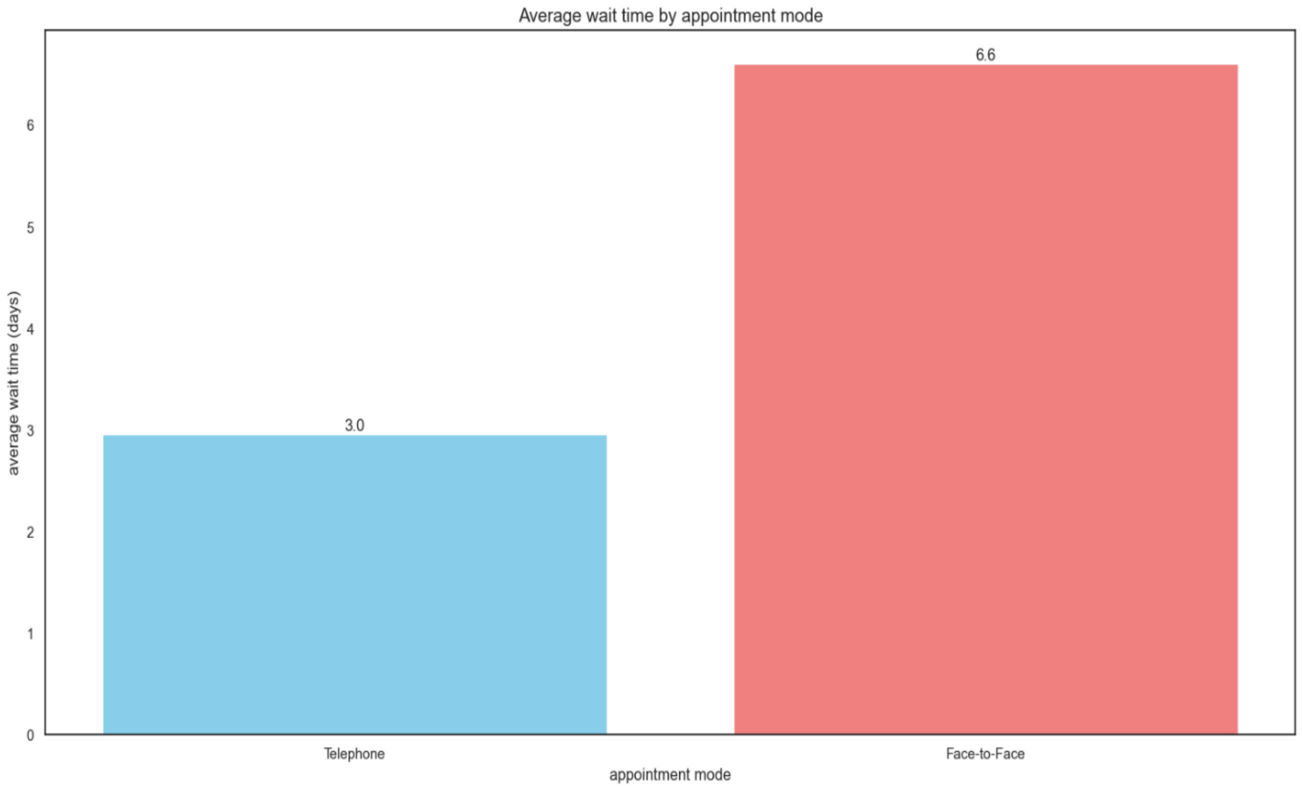
3. Visualization & insights

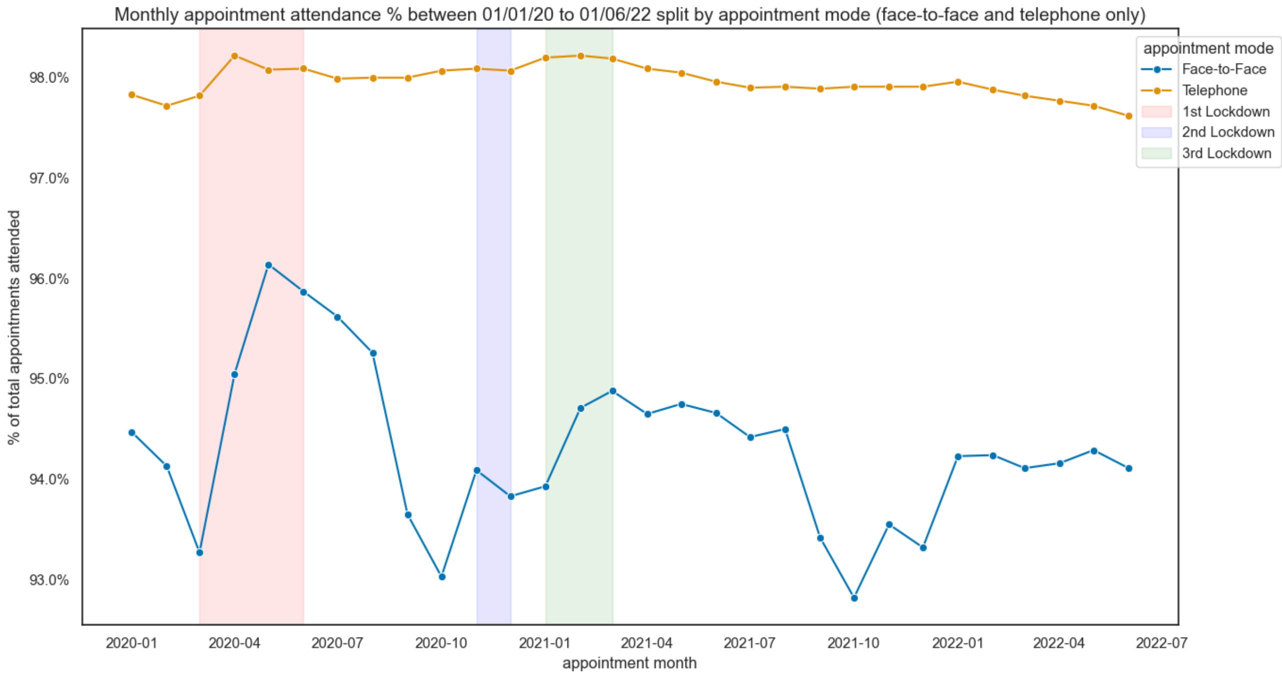
- Strong positive correlation between 'average wait time (days)' and 'DNA (did not attend) rate %'. **Pearson Correlation Coefficient = 0.89** & **P- value = 0.0075**. This result is statistically significant, meaning higher wait times are driving more missed appointments.



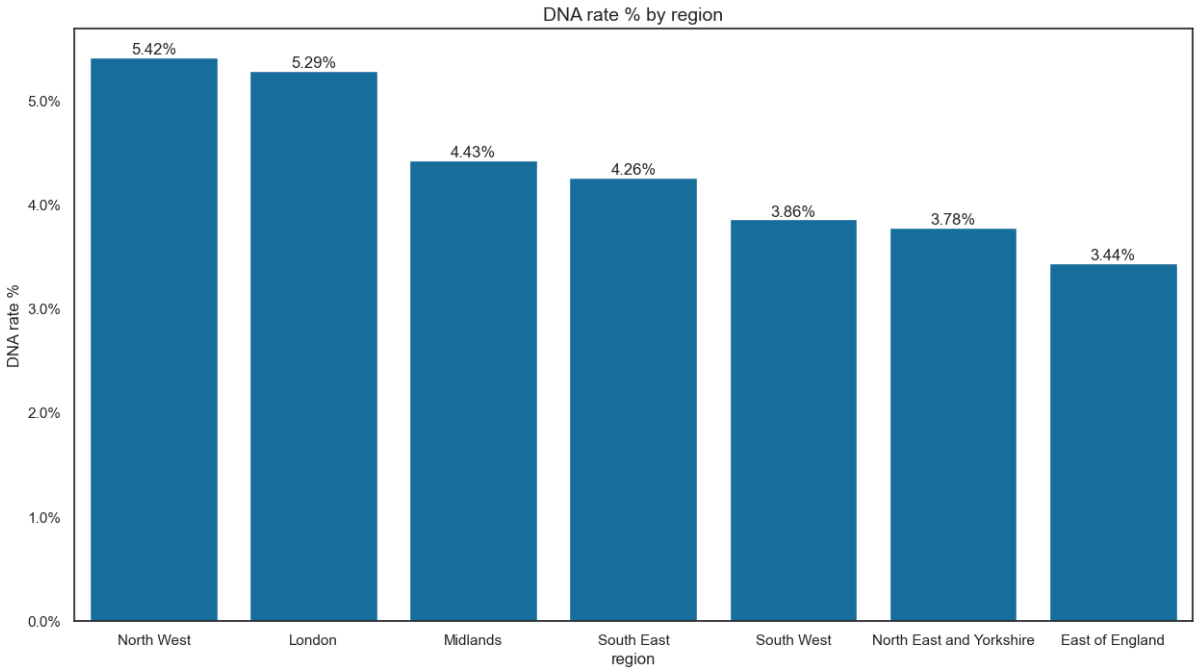
- Attendance rates are higher for telephone appointments across all wait times, but as wait time increases, the gap between telephone attendance and face to face attendance increases. A reason for this trend could be due to the average wait time being more than double for face-to-face appointments compared to telephone appointments.


Appointment attendance % between 01/01/20 to 01/06/22 split by appointment wait time and appointment mode for all icbs
% of total appointments attended
100.0%
97.5%
95.0%
92.5%
90.0%
87.5%
85.0%
82.5%
Same Day
1 Day
2 to 7 Days
8 to 14 Days
15 to 21 Days
22 to 28 Days
More than 28 Days
appointment wait time
appointment mode
Face-to-Face
Telephone

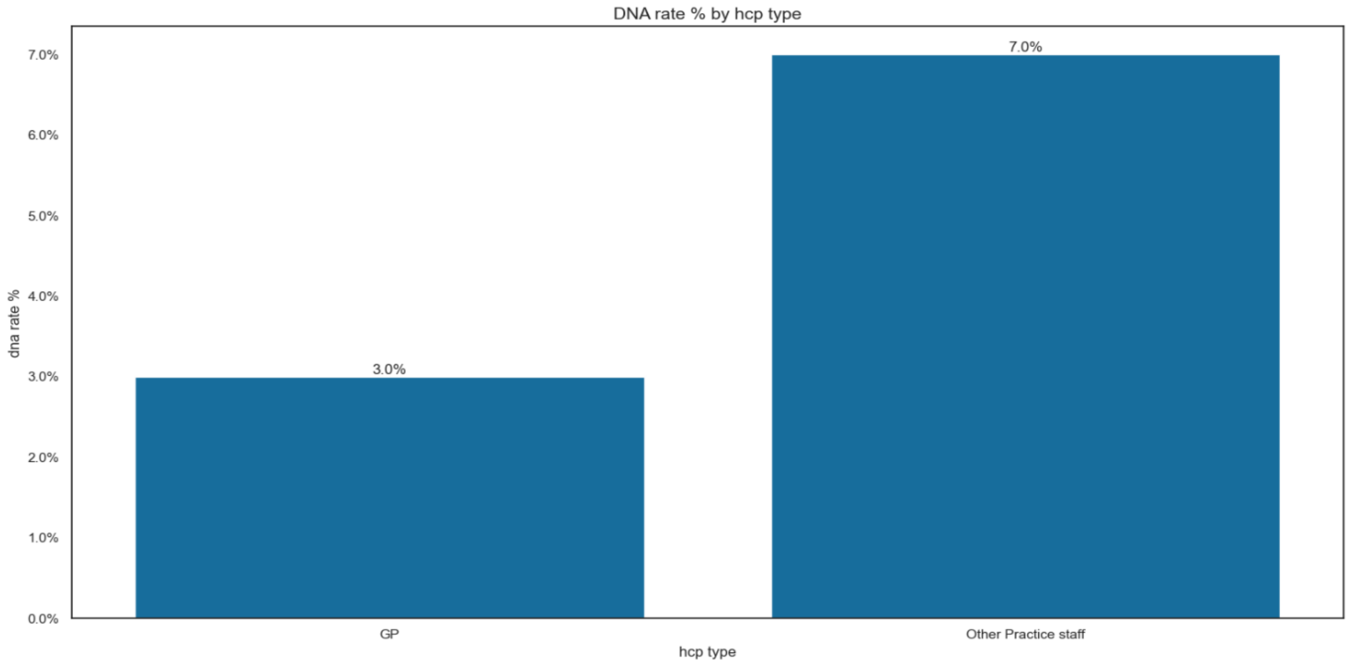

Average wait time by appointment mode
average wait time (days)
0
1
2
3
4
5
6
3.0
6.6
Telephone
Face-to-Face
appointment mode

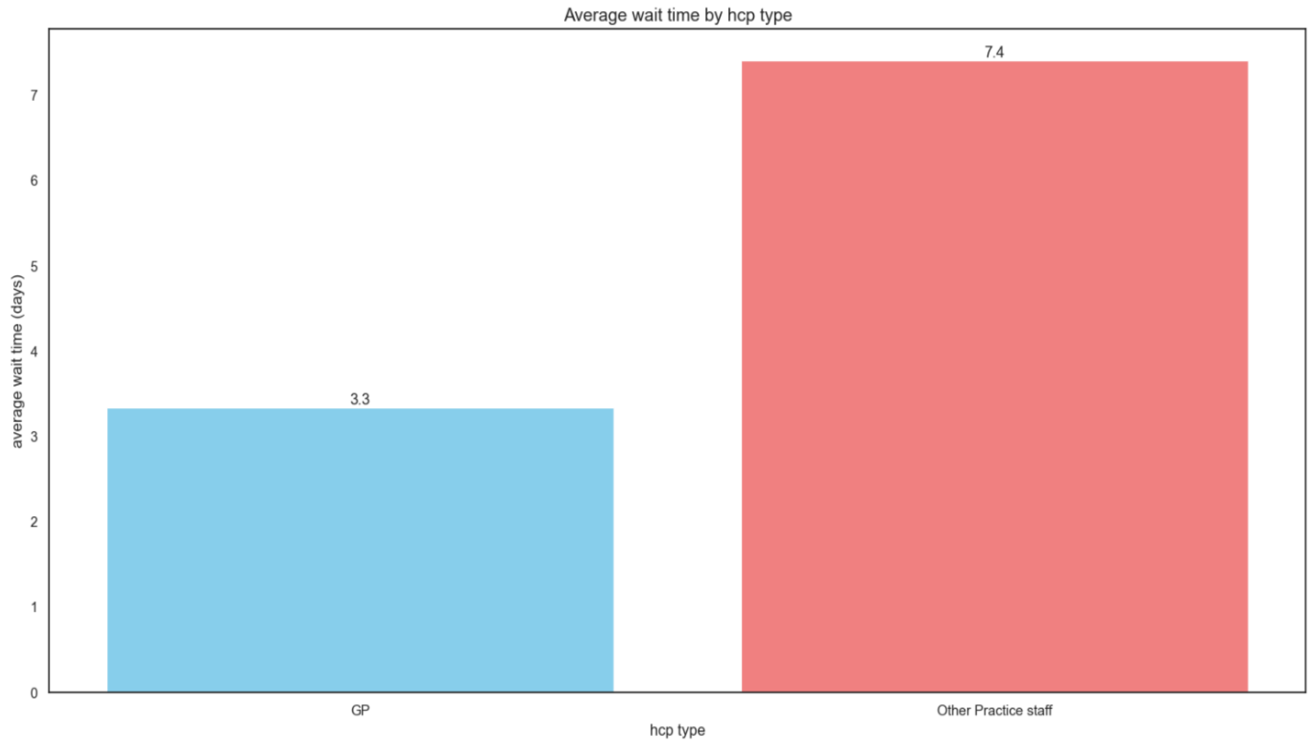


- 4.16% of total appointments are missed, which is costing the NHS £927M annually (assuming £30 per missed GP appointment) [1]. North West and London regions have the highest DNA rates.

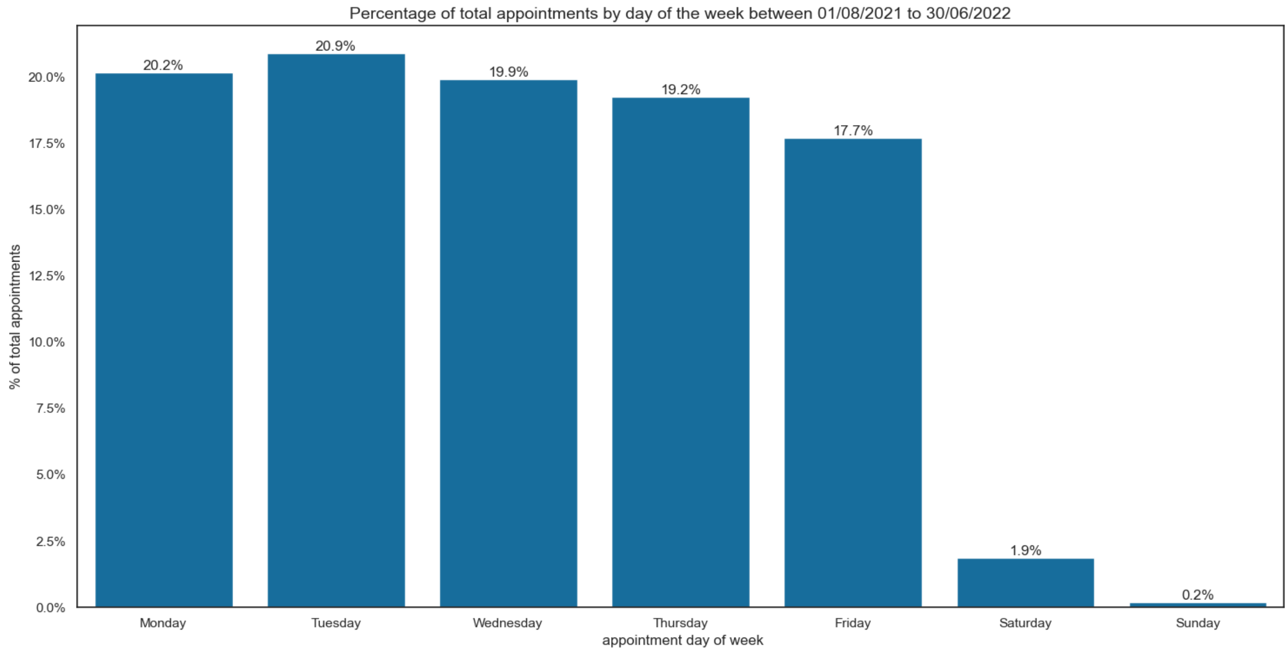


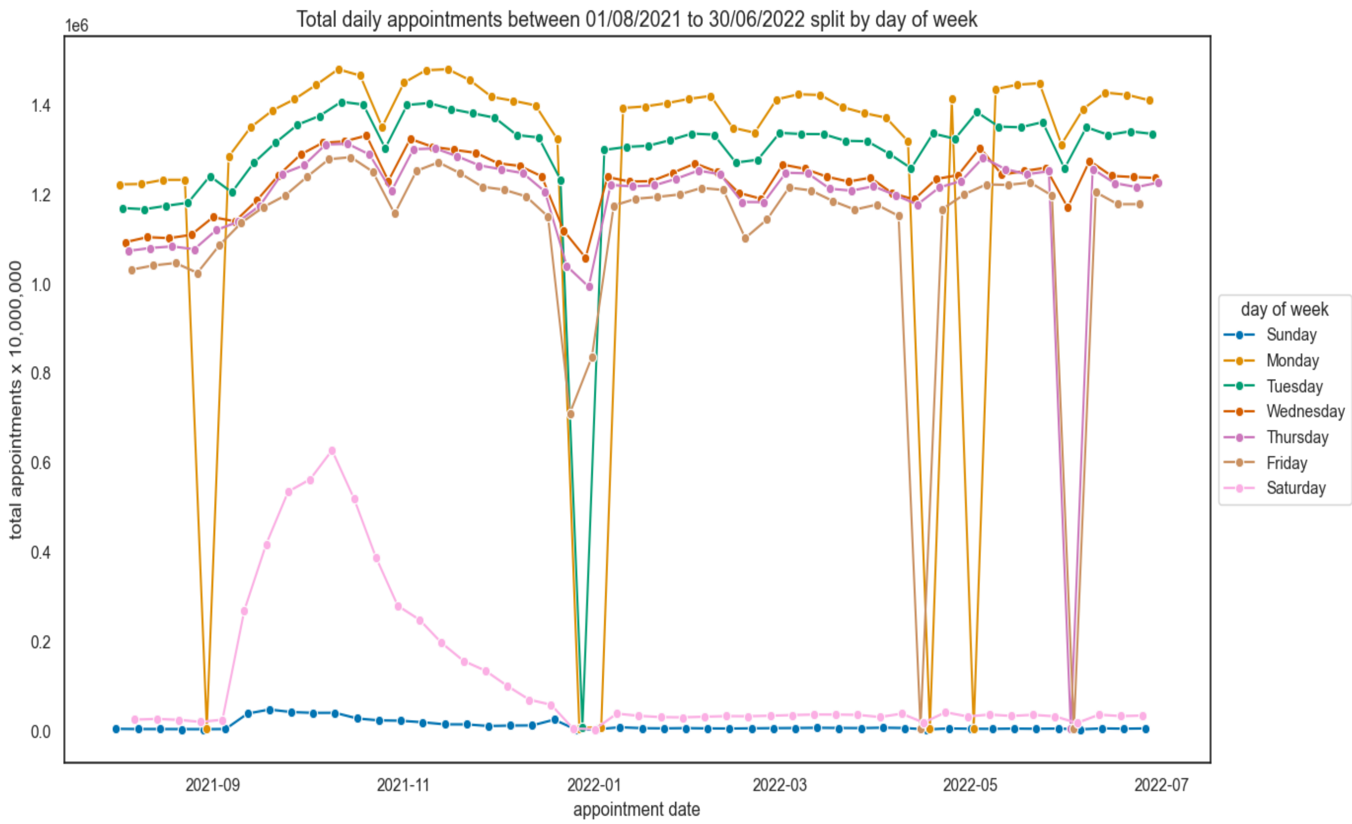
- Other Practice staff have more than double the DNA rate to that of GPs. A reason for this trend could be due to the average wait time for other practice staff being double to that of GPs.



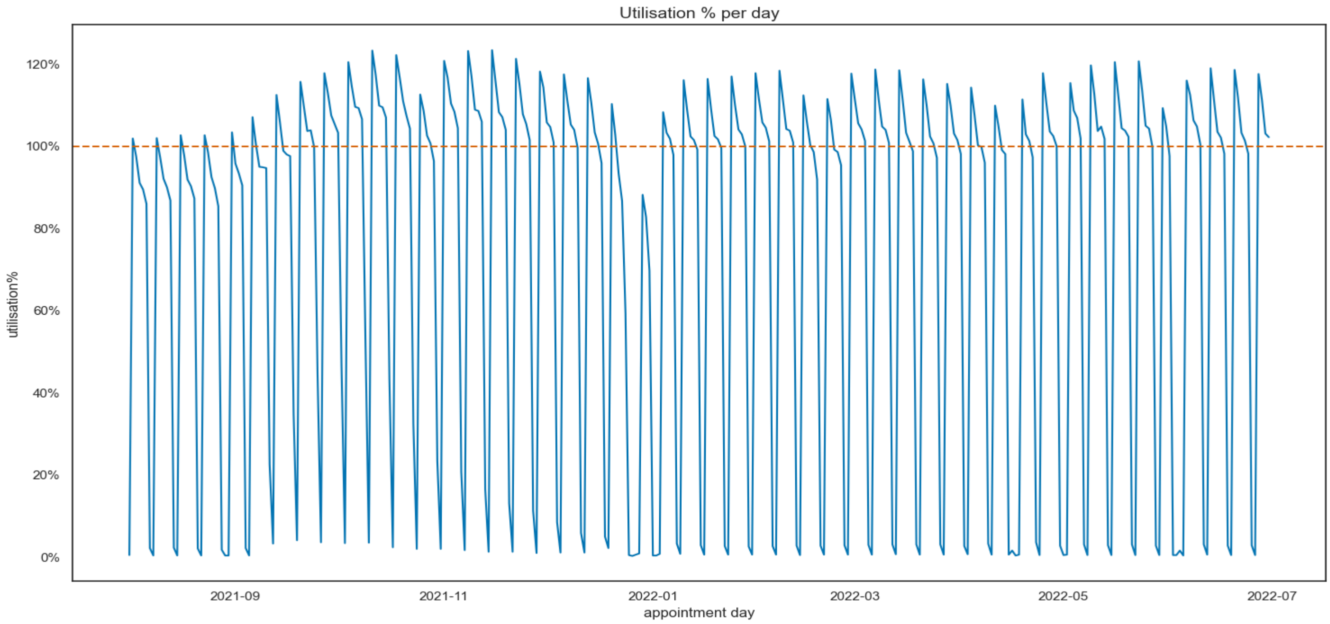


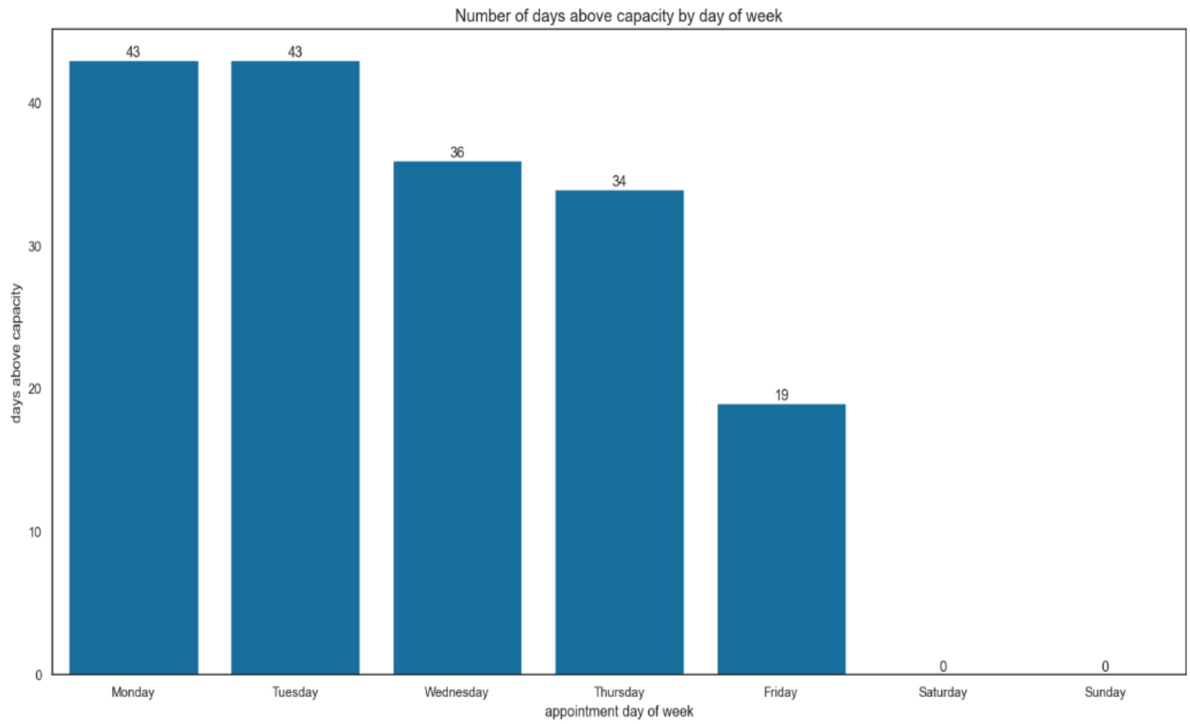
- Tuesday is the busiest day in terms of total appointments (20.9%), followed by Monday. The dips on weekdays relate to public holidays, otherwise Monday is the busiest.



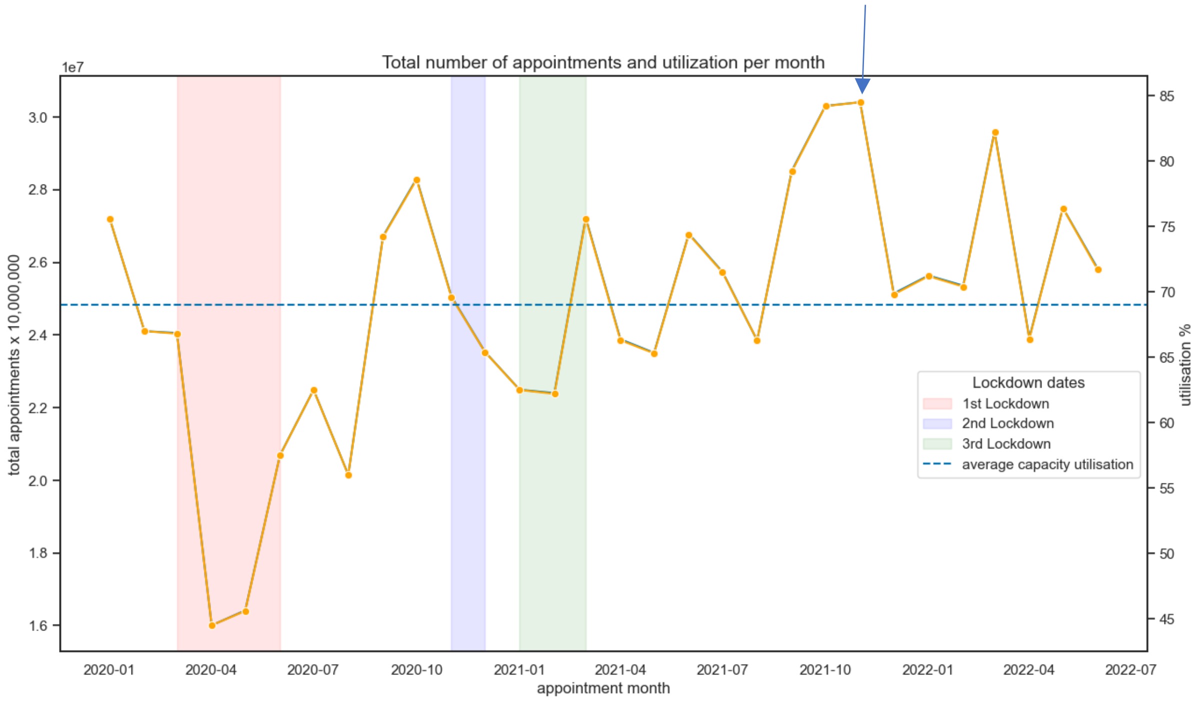


- The NHS, with a daily capacity limit of 1.2 million appointments, exceeded this capacity on 175 of the 334 days analysed (52%). Monday and Tuesday emerged as the most common days when capacity was exceeded.

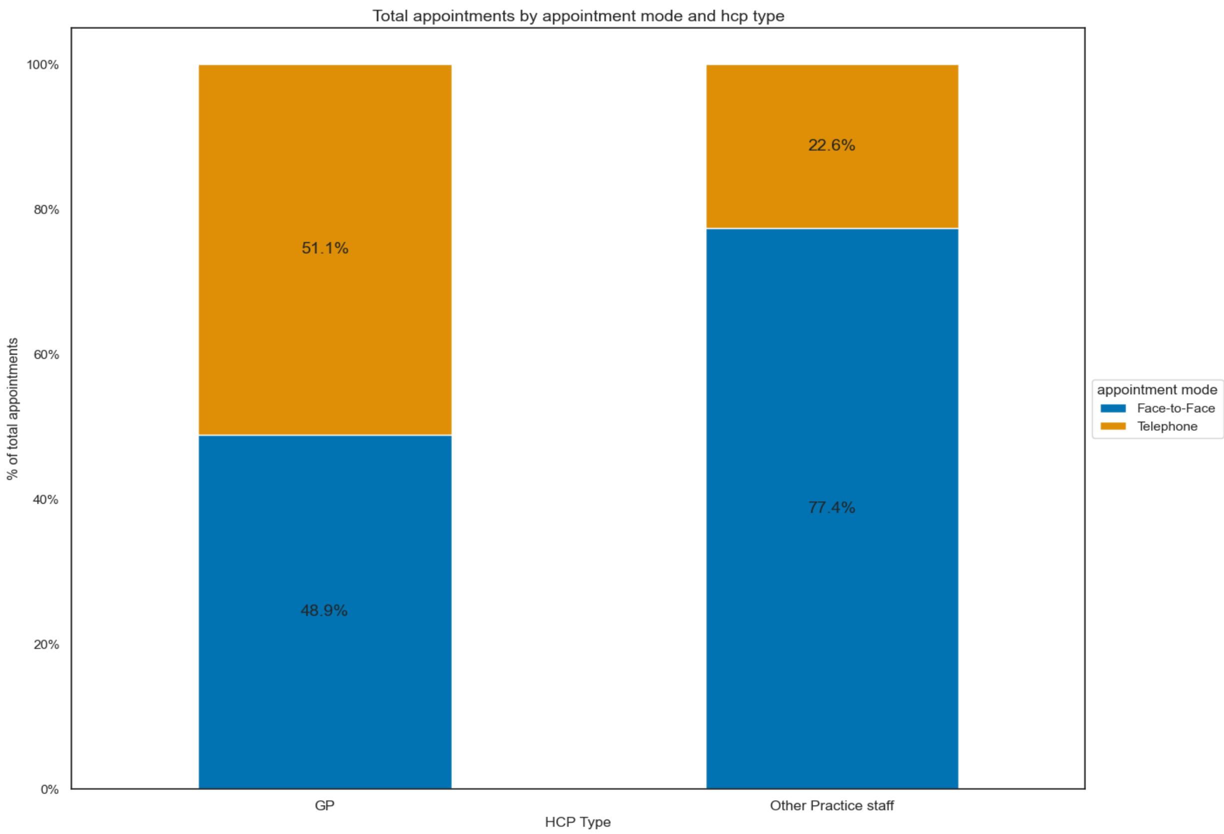




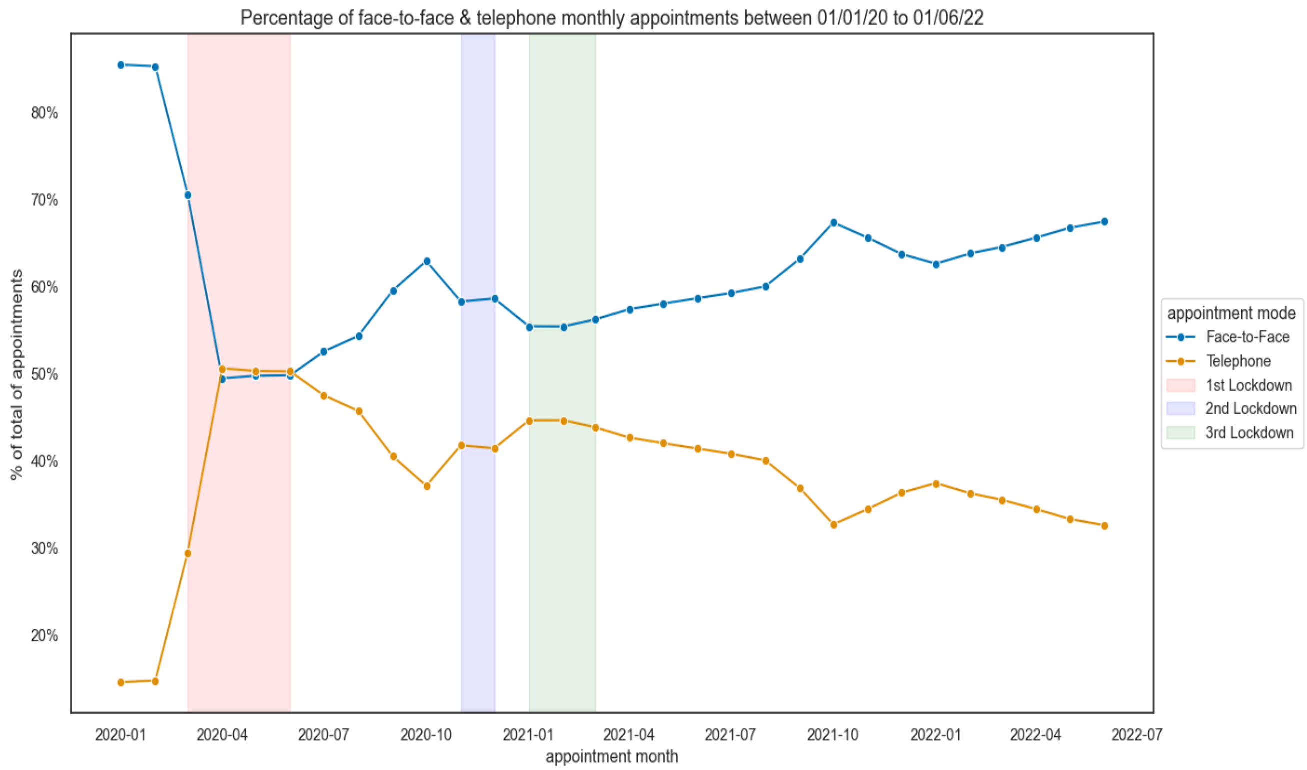
Maximum monthly capacity utilization = 84.5% in Nov21



- GPs handle 51% telephone, 49% face-to-face appointments which shows more favorability towards telephone. Other practice staff handle 23% telephone, 77% face-to-face showing the favorability towards face-to-face for other practice staff.



- Telephone appointments went from c15% in Jan20 to more common than face to face appointments in April20 at c50%. Since the first lockdown, face to face appointments have increased and telephone appointments have seen a decline.



4. Recommendations

1. **Incentivize more telephone over face-to-face appointments.** Attendance is greater for telephone appointments. A **limitation** is that we don't know what patients prefer telephone appointments, but if the data was enriched with patient data, the NHS could consider offering telephone appointments for patients more likely to miss face-to-face appointments.
2. **Keep time between booking and appointment short**. These appointments are more likely to be attended.
3. **Increase staff capacity earlier in the week**. Demand is highest on Mondays/Tuesdays.
4. **Monitor staff specific DNA rates**. Other Practice Staff have a higher DNA rate and average wait time compared to GPs, but they also conduct proportionally more face-to-face appointments. Consider expanding telephone appointments for Other Practice Staff to help reduce missed appointments.

Ultimately to meet population demands, increasing capacity is essential. However significant resource restructuring is necessary for more efficient utilization. Monthly utilization never exceeded 84.5%, suggesting that there was enough capacity. Finally, more years of data including pandemics, as well as of higher data quality would help enrich analysis and actionable insights.

(Total word count = 1100)

5. Appendix

Appendix 1a

Problem – There has been a significant increase in missed NHS appointments which has increased costs for the NHS and led to a misallocation of resources.

Q1 – Why has there been an increase in missed NHS appointments?

Answer – Because patients are not attending their appointments.

Q2 – Why aren't patients attending their appointments?

Answer – This could be due to a number of issues, i.e. transportation issues obstructing patients from attending their appointment, lack of awareness meaning patients forgetting they have an appointment, long wait times meaning patients decide withdrawing from their appointment.

Q3 – Why do patients encounter the above issues in attending their appointments?

Answer – Lack of accessible transportation, patients not receiving timely reminders/miscommunication about appointment, inconvenient appointment times.

Q4 – Why are timely appointment reminders/miscommunication between the NHS and patient, and inconvenient appointment times not properly addressed by the NHS?

Answer – The current appointment system may lack robust appointment reminder mechanisms and the system may be inflexible in scheduling more appropriate times for its patients.

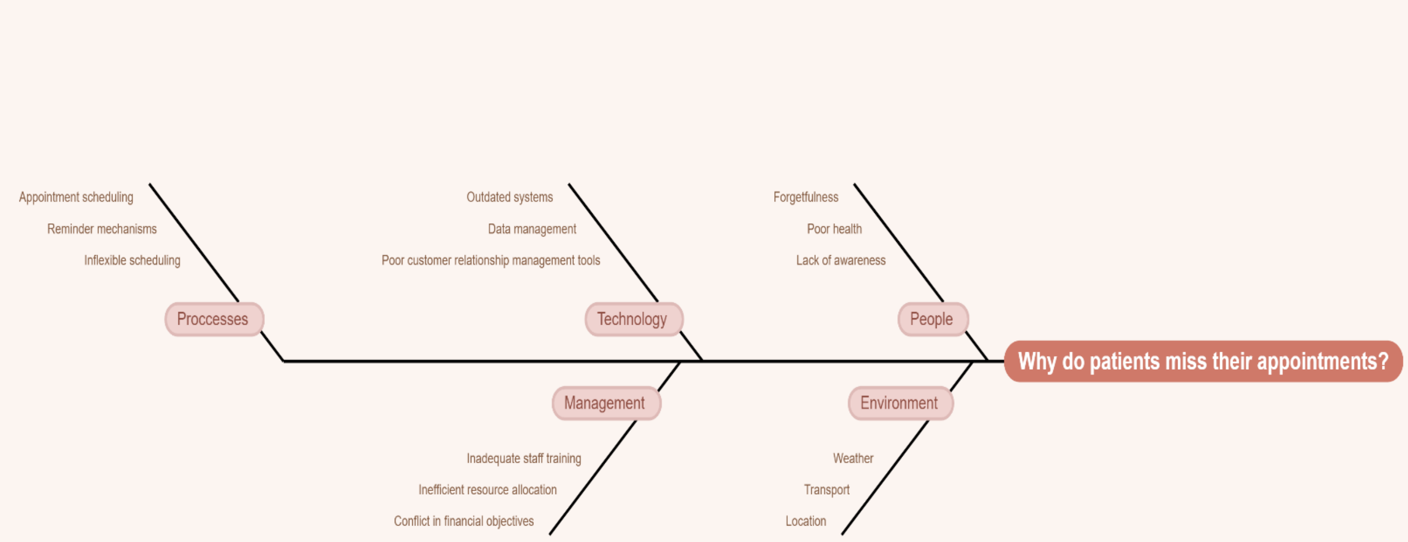
Q5 – Why is the current appointment system not robust and inflexible in scheduling appointments and communicating with patients.

Answer – Because there is limited investment into data and technology which could allow for automated reminders to be communicated to patients and potential for scheduling appointments at more convenient times.

Root cause – The root cause of the increase in missed appointments is due to lack of investment in technologically advanced data management systems which could send automated reminders to its patients and provide more flexibility in appointment scheduling.

Appendix 1b

Fishbone diagram of root cause analysis



Why do patients miss their appointment?

1. **People**
    - Forgetfulness – Patients may forget they have booked an appointment
    - Poor health – Patient might be sick or too unwell to attend appointment
    - Lack of awareness – Patient lacks understanding of keeping their appointment
2. **Environment**
    - Weather – Adverse weather conditions preventing patients from attending appointment
    - Transport – Poor transport links to appointment location
    - Location – Medical centre/clinics located too far from residential areas
3. **Technology**
    - Outdated systems – Old systems not flexible in appointment scheduling and tracking
    - Data management – Poor standard of data entry leading to data quality issues and unmapped data
4. **Management**
    - Inadequate staff training – Limited training for staff on managing patient appointments
    - Inefficient resource allocation – Little resource allocated to patient communication and management of appointments/reminders
    - Conflict in financial objectives – Trust leaders having conflict in priorities and where public funds should be spent
5. **Processes**
    - Appointment scheduling – Complex appointment scheduling process [2]
    - Reminder mechanisms – Ineffective or absent reminder systems
    - Inflexible scheduling - Limited availability for rescheduling or cancelling

Appendix 2a – Preparing my workstation

```
# Import the necessary libraries.
import pandas as pd
import numpy as np
import datetime as dt
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.ticker as mticker
from scipy.stats import pearsonr
import scipy


# Display plots within notebook
%matplotlib inline

# Ignore warnings.
import warnings
warnings.filterwarnings('ignore')

# Set figure style
sns.set(style = 'white', palette = 'colorblind')
```

Appendix 2b – Sense checking data checklist

The below were combined into a user defined function to validate the data more efficiently

1. df = pd.read_csv('csv.csv') *# read the csv file*
2. df.shape *# display number of rows, columns in the data frame*
3. df.isnull().sum() *# determine the total number of missing values*
4. df.dtypes() *# determine data types*
5. df.duplicated().sum() *# determine the total number of duplicates*
6. df.describe() *# determine the numerical data with basic statistics*

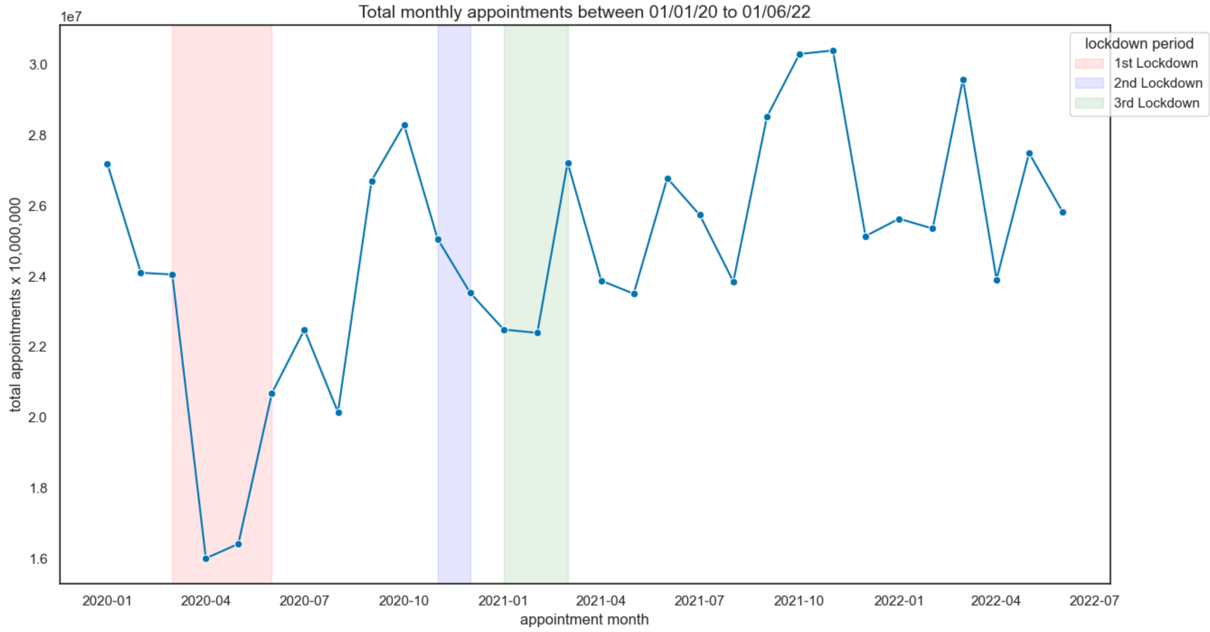
Data Validation

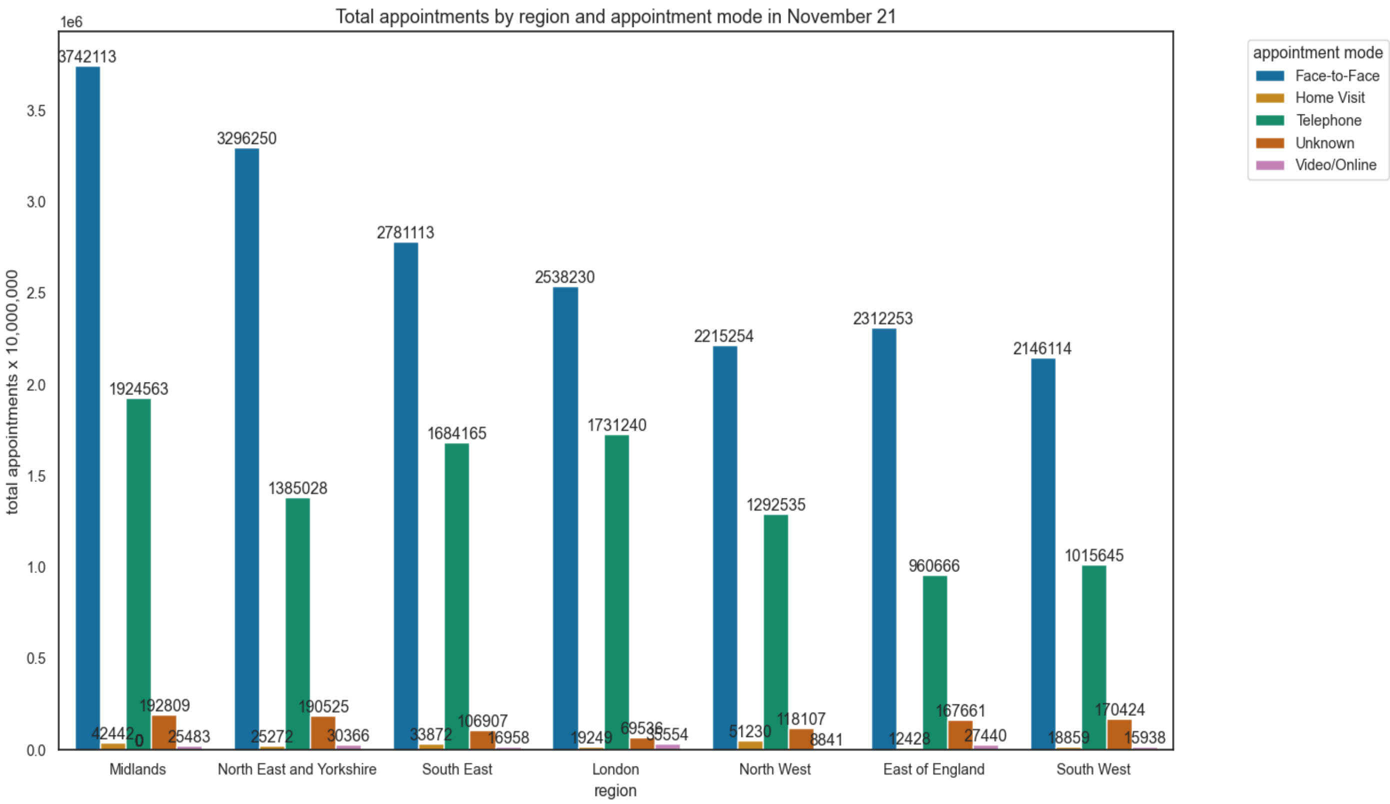
```
def validate_data(df):
    """
    Performs basic data checks on a Pandas DataFrame.

    Args:
        df: The Pandas DataFrame to validate.

    Returns:
        A dictionary containing the results of the data checks to easily access individual elements
    """

    results = {}

    results['shape'] = df.shape  # determine number of rows and columns in the df
    results['null_values'] = df.isnull().sum()  # determine number of null values
    results['data_types'] = df.dtypes  # determine column data types in the df
    results['duplicate_values'] = df.duplicated().sum()  # determine number of duplicates in the df
    results['summary_statistics'] = df.describe()  # view summary statistics in the df

    return results
```

Note - I would normally consider renaming the columns for ease of use as standard practice in the importing routine. However, I retain the original column names for two reasons:
Familiarity with NHS naming conventions among stakeholders and ease of code replication for future or historical data.

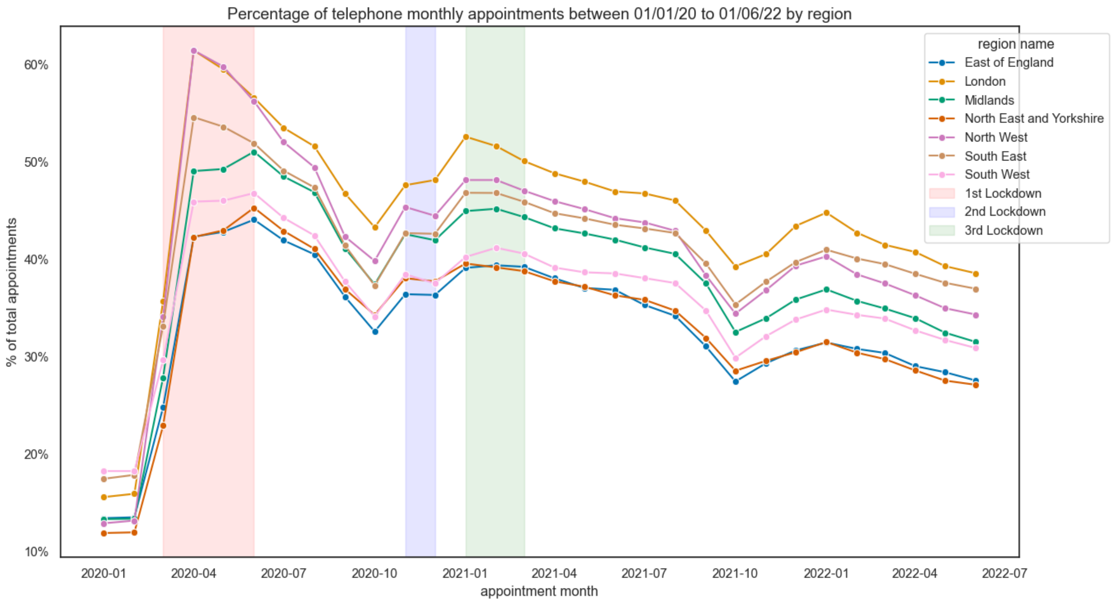
Appendix 3 – Further insights and visualizations

- Autumn is the busiest season, with November 21 being the period with the highest number of appointments (4.1%). Midlands was the region with highest number of appointments, specifically face-to face during this period.

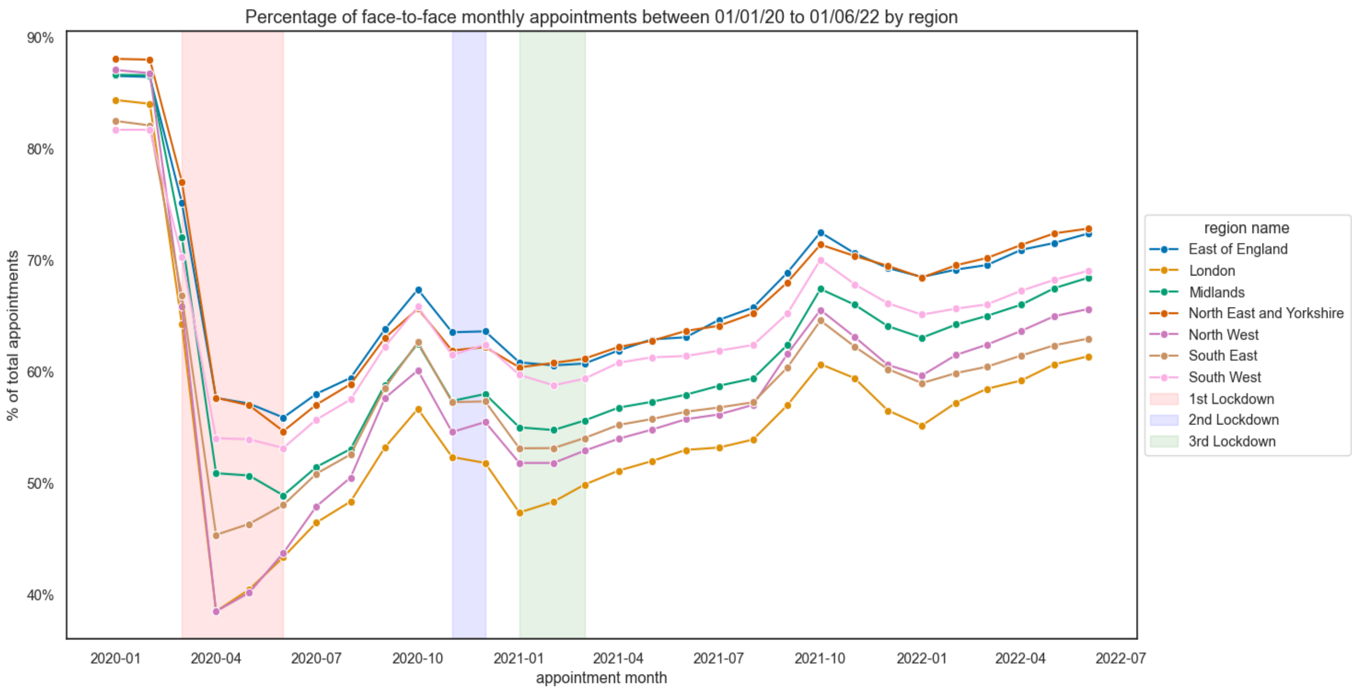




- London tops the region with the most telephone appointments, but it is the region with the second highest DNA rate (5.26%). This is an interesting observation, as you'd expect London to have more face-to-face appointments given it is mostly urban. I would expect rural places to have higher telephone appointments. This potentially tell us that there is a need to understand regional dynamics.



- Huge decline for face-to-face appointments across all regions at the start of the first lockdown, with East of England leading the way with the most face-to-face appointments, peaking at c70% in Oct21. North West, Midlands, South west interestingly saw a rise in face-to-face appointments in the second lockdown, and nearly all regions saw an increase in face-to-face appointments in the third lockdown.



Appendix 4 – Limitations & Next steps

Limitations/Analytical recommendations

1. Data quality i.e. unmapped values, unknown appointment wait times, unknown attendance statuses, unknown hcp types, unknown appointment modes. Duplicates in the 'appointment regional' dataset, null values in the Twitter dataset. This all makes it difficult for accurate analysis as unknown values don't help us understand the picture in full detail and are meaningless.
2. Capacity is a given as a general figure, better to have capacity at ICB level. Also, would help to know capacity per the actual resource categories themselves for greater insight (i.e. appointment mode, hcp type etc.)
3. Appointments data with a larger date range would give a fairer, more balanced assessment.
4. Omission of patient data i.e. how many patients per ICB/region to understand capacity utilization at a more granular level.

Next steps / Areas for exploration to help enrich analysis

1. Implement Predictive Analytics by using past appointment data to identify patients at high risk of missing appointments and offer them extra reminders or flexible slots.
2. Collect more granular data on the appointments carried out by 'other practice staff' to allow a better understanding of resource use.
3. More granular information on the role of the health care professional associated with the appointment to better understand resource and capacity.
4. Appointment mode offered VS appointment mode accepted to understand patient behavior i.e. was the patient offered an online booking, and what was the actual mode they chose in the end?
5. Go beyond identifying trending hashtags to perform deeper sentiment analysis and natural language processing to extract themes and sentiments from patient feedback or social media that can explain public perceptions.
6. Enhanced Patient Communication: Explore the effectiveness of different communication channels (e.g., SMS, email, phone calls) in reducing missed appointments. Implement and evaluate automated reminder systems and their impact on appointment attendance.
7. Integration with External Data Sources: Integrate weather data, local events, and transportation information to understand external factors affecting appointment attendance. Use socio-economic and demographic data to identify vulnerable populations and tailor interventions to their specific needs.
8. Detailed Geographic Analysis: Conduct a more granular geographic analysis to identify specific areas with high missed appointment rates and resource constraints. Implement localized strategies to address the unique challenges of different regions.

Appendix 5 – Analytical sub questions

1. Has there been adequate staff and capacity in the networks?

- How many staff are employed at each service setting?
- Number of healthcare staff per patient?
- How does staff availability correlate with appointment availability/missed appointments?

2. What was the actual utilisation of resources?

- What is the total number of appointments per service setting, location, and context type?
- What percentage of scheduled appointments were attended versus missed?
- How do utilization rates vary across different national categories and service
- settings?

3. Data characteristics and trends

- What is the date range of datasets?
- Which service setting reported the most appointments in the specified period?
- What is the distribution of locations, service settings, context types, national categories and appointment statuses in the data sets?

4. Appointment patterns

- Comparison of staffing and appointment capacity across regions or networks?
- What is the monthly and seasonal trend of appointments across different service settings and context types?
- Are there any noticeable trends in appointment statuses over time?

5. Insights from Missed Appointments

- What are the most common reasons for missed appointments?
- How do missed appointments vary by service setting, location, and time period?
- What is the financial impact of missed appointments on the NHS?

6. Twitter Data Insights:

- What are the top trending hashtags related to NHS services?
- How can sentiment analysis of tweets inform decision making?
- How is the data collected; has it been collected ethically?

Appendix 6 – General insights from data

Question 1: How many locations are there in the data set?

- Number of regions = 7
- Number of Integrated Care Boards (ICBs) = 42
- Number of Sub Integrated Care Boards (Sub ICB) = 106

Question 2: What are the 5 locations with the highest number of appointments?

- The top five sub ICB locations are North West London, North East London, Kent and Medway, Hampshire and Isle of Wight, and South East London.
- This is the case in both the nc and ad Data Frames, but note there are fewer records in ad than nc .
- The top ICB location is North East and North Cumbria ICB.

Question 3: How many service settings, context types, national categories, appointment statuses are there?

- Number of service settings = 5 (91% of appointments in General Practice)
- Number of context types = 3 (87% of appointments in Care Related Encounter)
- Number of national categories = 18 (33% of appointments in General Consultation Routine which is most common)
- Number of appointment statuses = 3 (91% of appointments attended, 4% DNA, 5% unknown)

Question 4: How are the appointments delivered?

- Number of appointment modes = 5 (59% of appointments face-to-face, 36% telephone are most common)

Question 5: When are these appointments being delivered?

- Number of time between booking and appointment intervals = 8 (46% on same day, 20.7% taking place within 2-7 days are most common)

Question 5: Who is delivering these appointments?

- Number of HCP types = 3 (51% for GP and 46% for Other Practice staff)

Question 6: How long do the appointments last?

- Number of actual duration intervals = 7 (24% of appointments are of unknown length; 20% are 6-10 minutes long and 17% are 1-5 minutes long.)

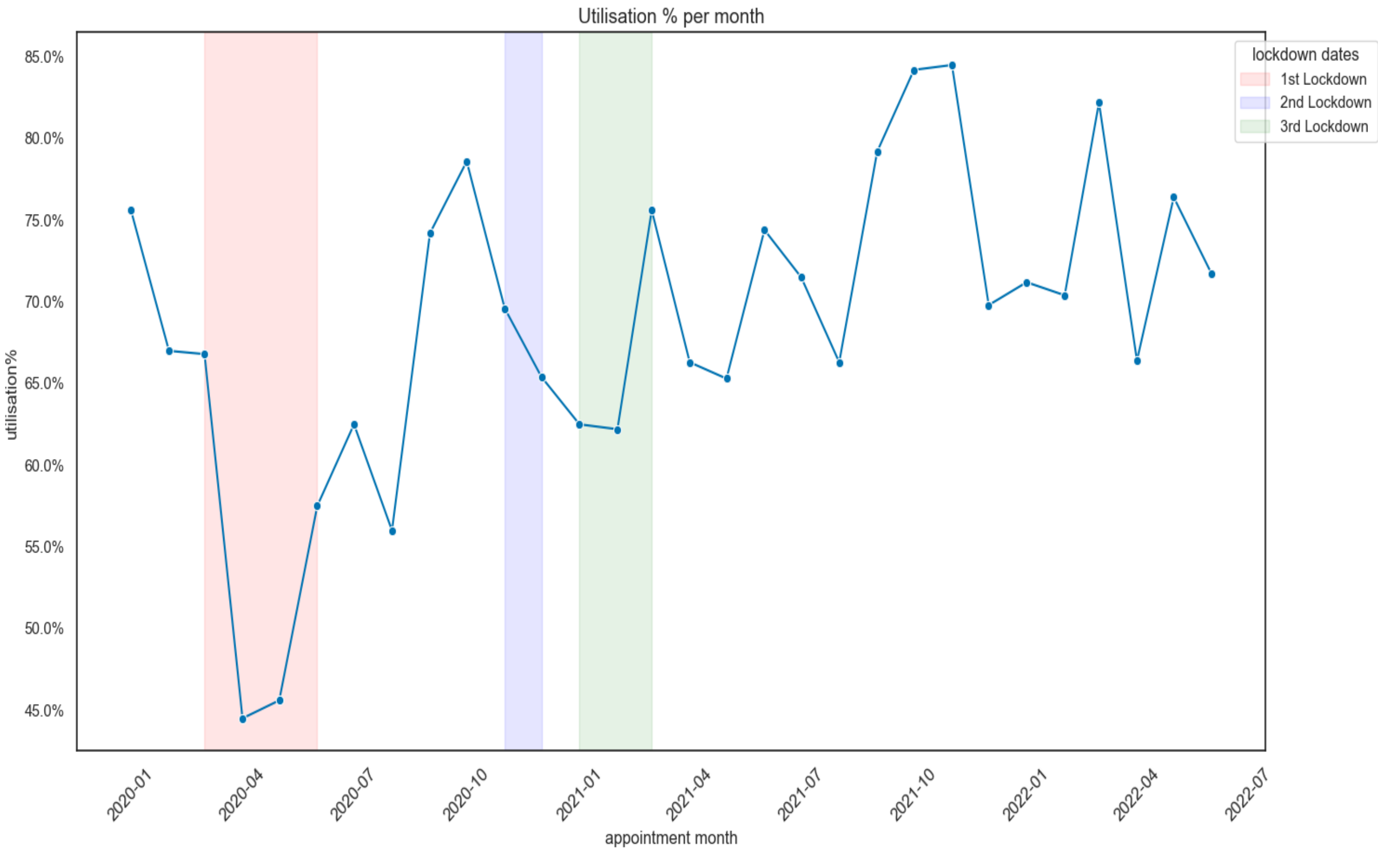
Appendix 7 – Capacity/ Utilization analysis

Average capacity utilization for the NHS is around 69% for the provided date range. But it is erroneous to think of capacity as simply the number of beds available. Capacity includes all equipment and staff that are needed to provide health care across all healthcare settings [3]

Using the appointments regional dataset, I created a new data frame to aggregate the total number of appointments per month and calculate the utilization of services based on the NHS guideline of a maximum daily capacity of 1,200,000 appointments.

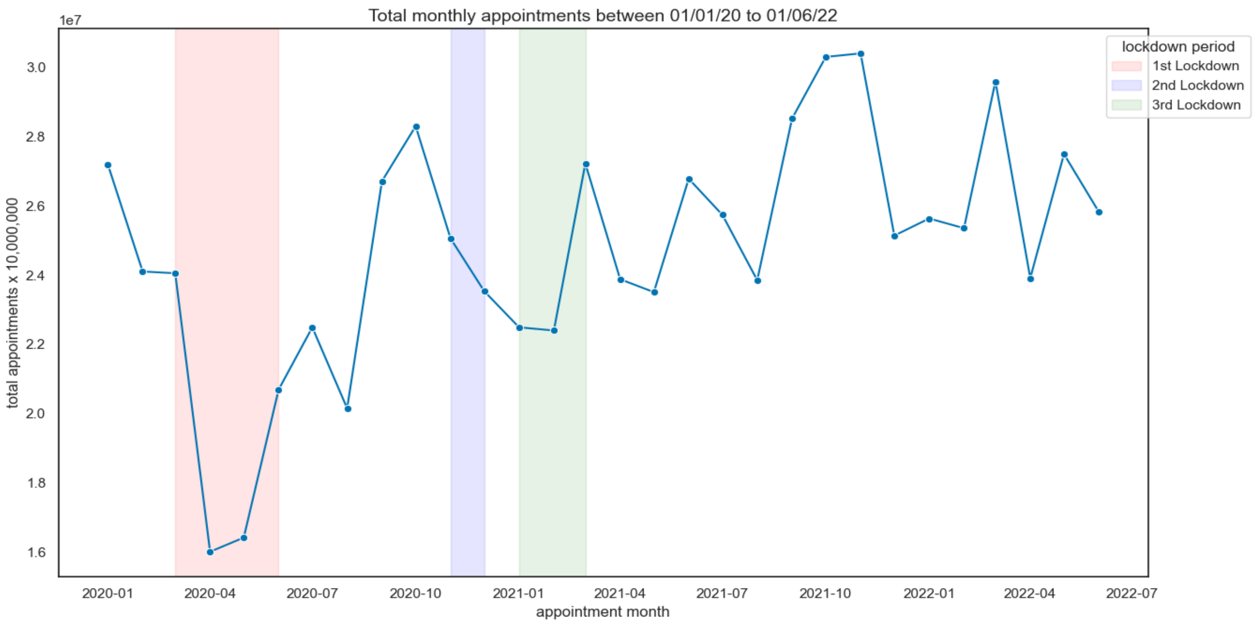
The utilization is calculated by dividing the monthly appointments by the product of the assumed average days in a month (30) and the daily capacity, and then multiplying the result by 100 to express it as a percentage. From the graph below we can see that the NHS coped quite well and utilization never exceeded 84.5% capacity, suggesting that there was enough capacity.

However, it is important to note this data does not take into account any disparities during pandemics and seasons, which affects capacity and utilization. This is not something which we can analyze with the provided data, but it would be of more value to inform the NHS of any changes it needs to make to provide better services.

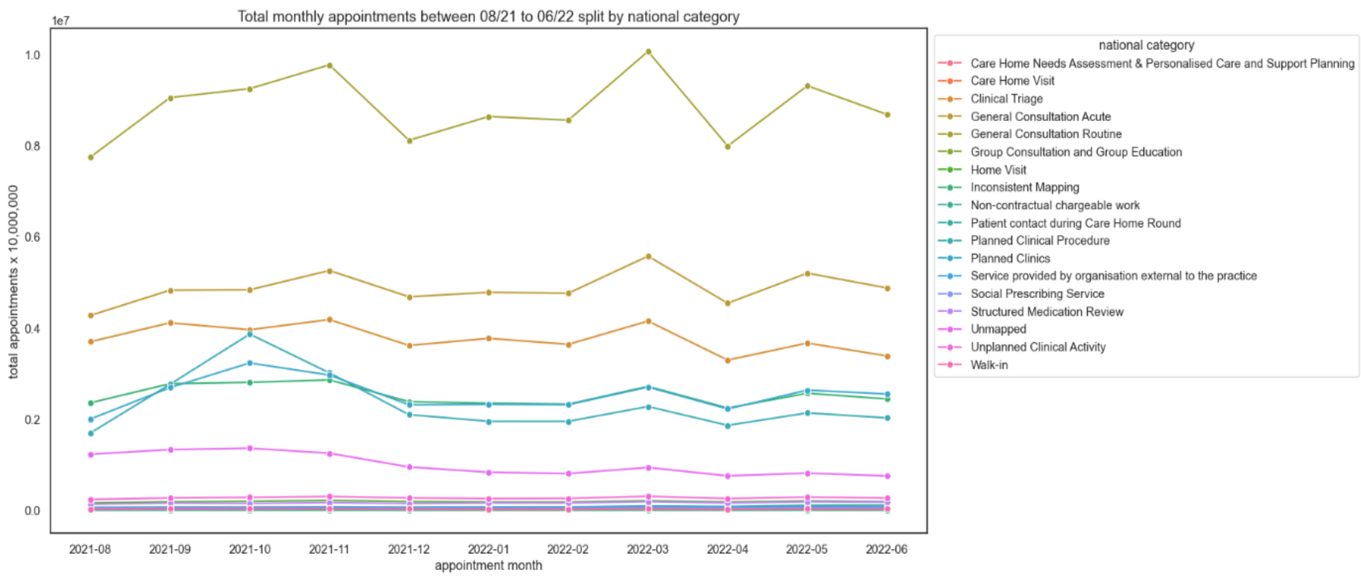


Appendix 8 – Covid analysis

The UK went into its 1st lockdown for Covid on 26th March 2020, and then regional restrictions were in place from May 11th 2020. The UK went into its 2nd lockdown on 5th November 2020 till 23rd December 2020. The UK went into its 3rd lockdown on 4th January 2021 till 8th March 2021. As restrictions were eased, the NHS decided to postpone non urgent treatments to reserve capacity for Covid patients and those needing planned clinical procedures. This is all shown by the dips in October 2020 - February 2021, May 2021 and spikes in November 2021.



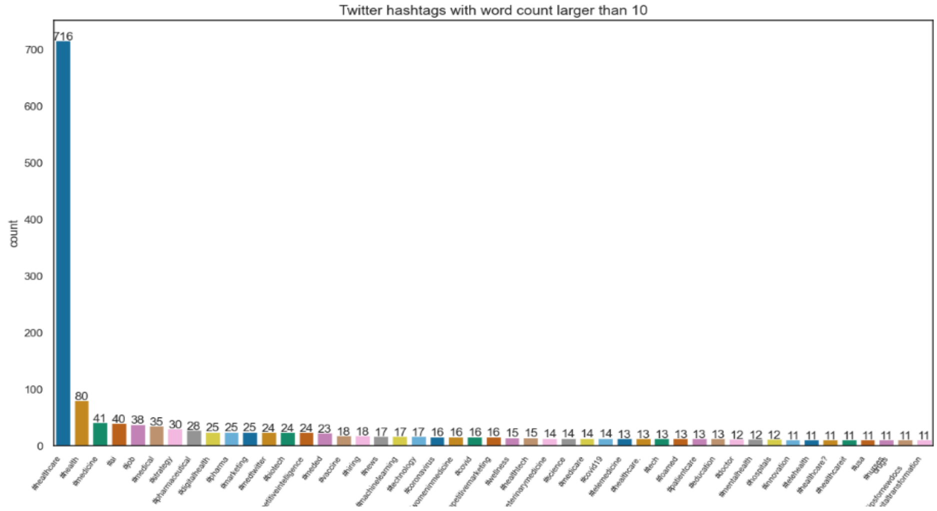
With the backlog of cancer and urgent treatments increasing, we observe a spike in 'planned clinical procedures' and 'planned clinics' in October 2021, as seen below in the appointments by national category graph.



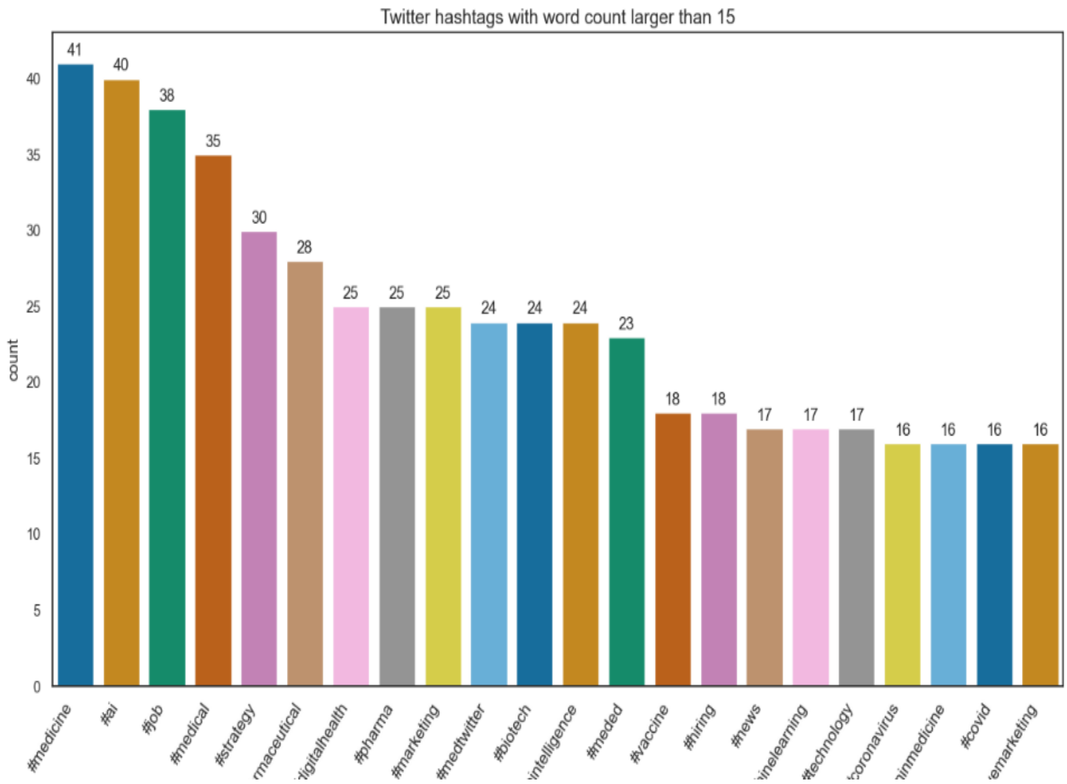
Appendix 9 – Twitter analysis

<u>How can the NHS utilize tweets to provide feedback to stakeholders</u>

Using the twitter data provided to us, an effective way to gather sentiment is analysis of twitter hashtags. Using Python, we were able to extract information on hashtags and the number of times they were used. Below is a graph of top 10 hashtags that have a count larger than 10.



The above graph shows the disparity between the #healthcare hashtag and all the others. This is not really useful, so we'll explore a new graph that has 'counts' more than 15 and exclude the 2 overused hashtags #healthcare and #health to get a more representative sample.



This is a much clearer graph and allows us to get a better idea of sentiment. Key topics of engagement include:

- AI/technology/machine learning/digital health/biotech. This tells us that there are many views on digital transformation in the health industry on twitter.

In general, the most frequently used hashtag is #healthcare with 716 occurrences, followed by #health (80), #medicine (41), and #ai (40).

Do these hashtags add value to the overall project?

Although we get an idea of what people are talking about and what maybe 'trending', these tweets don't actually reveal anything useful to the NHS and don't address the 2 main business questions that we set out at the start of this report. To remind us again, they are:

1. ***Are there adequate staff and capacity in the networks?***
2. ***What is the actual utilization of resources?***

Also, there is the topic of ethically sourcing this data using web scraping. A report conducted by UCL [4] on using twitter in research analysis argues that seeking consent from twitter and every individual is impractical. There is also the case of data protection and GDPR laws in Europe that need to be addressed.

There are also evident biases in the people who use Twitter. Twitter usage is shown to mostly popular in younger groups and minority ethnic populations, thus collecting a representative sample to carry out a fair analysis is problematic.

In conclusion, Twitter can be a valuable resource for the NHS to understand public engagement and service utilization. However, rigorous data cleaning, geographically relevant hashtag analysis and ethical considerations are paramount. Limitations, such as inherent biases in Twitter data and potential for misinterpretation, must be carefully addressed to ensure reliable and meaningful insight.

Appendix 10 – GitHub

This project will be hosted on GitHub, which is one of the largest coding communities in the world. There are several benefits of sharing my work on GitHub, including: version control for code with a visual interface, easy collaboration with multiple contributors on projects, a built-in issue tracker, backup of code files, the ability to reproduce work and access to a large open-source community through features like forking and pull requests; making it a valuable tool for managing and sharing code across teams and projects. This also fosters innovation to solve our business problem more efficiently.

You can view my GitHub repositories by pressing the below link:

GitHub - https://github.com/harshdeepkohli53

References:

1. *NHS England: NHS England. (2019, January). Missed GP appointments costing NHS millions. Retrieved from https://www.england.nhs.uk/2019/01/missed-gp-appointments-costing-nhs-millions/*

2. *Salisbury, C., et al. (2021). The impact of a quality improvement (QI) program on missed appointments in general practice. British Journal of General Practice, 71(702), e31-e39. https://doi.org/10.3399/bjgp21X101569*

3. *NHS Providers: NHS Providers. (n.d.). Mapping the NHS winter: Capacity. Retrieved from https://nhsproviders.org/mapping-the-nhs-winter/capacity*

4. *UCL Data Protection: UCL Data Protection. (n.d.). Guidance for staff, students and researchers: Research: Research registration guidance. Retrieved from https://www.ucl.ac.uk/data-protection/guidance-staff-students-and-researchers/research/research-registration-guidance*