


Chapter 10


Public Perception of the Portuguese National Health Service: A Social Media Sentiment Analysis Approach

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ABSTRACT

Analysing social media testimonials about public health is vital for understanding public perceptions and emotions, leading to better policy-making and health services. This investigation reviews recent research on sentiment analysis in healthcare, focusing on public perception of the Portuguese National Health Service (NHS) through interactions on its Instagram and Facebook pages. Using a Machine Learning approach, the study finds a negative perception of the NHS, posing a high reputational risk. It recommends persistent institutional mediation through comments and systematic sentiment analysis to monitor social media opinions, improve communication, and refine policies based on real-time feedback.

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1. INTRODUCTION

The Portuguese National Health Service is subject to enormous pressure and scrutiny from the population, both as users and taxpayers, as a result of the limitations and negative impacts of the various contemporary problems that condition its response, from the underfunding of its activity to the difficulty of attracting the necessary human resources, namely specialist doctors, to the ageing of population and the increase in healthcare needs, as well as the costs of treatments, especially innovative ones, which forced a concentration of resources on mitigating this disease and ended up letting others evolve (Varanda *et al.*, 2020).

There are also two major political conceptions regarding the organization of the Portuguese National Health Service, which are diametrically opposed, namely one that defends an exclusively public component and one that considers the presence of the private and social sector, with the latter having various positions on the proportion of this division (Simões & Fronteira, 2021).

Therefore, it can be argued that this dichotomy between a universal service and its inability to find a timely response for everyone, given the high demand and finite resources, generates divergent sentiments. It is these feelings that this work aims to capture, describe, understand, and propose strategies for decision-makers (Hespanha, 2019).

The Portuguese National Health System comprises, in global terms, three major components: public, private, and social sectors (Simões & Fronteira, 2021). The public sector includes the National Health Service, created in 1979, comprised of public institutions that provide healthcare, the regulatory and inspection institutions, and central and regional entities of the Ministry of Health that work in the areas of health promotion, prevention, health authority, governance, financing, technology and, among others, the activity carried out under their responsibility through partnerships, conventions, contracts and other agreements with the other two sectors. The private sector includes all private healthcare providers, whether companies or individuals. The social sector includes all the mercy, mutual organisations and other private social solidarity institutions that provide healthcare. The Portuguese National Health Service (NHS) is based on the Beveridge model, with universal access for citizens, tending to be free of charge and financed by the state through taxes (Tavares & Marques, 2021). The NHS is not an entity with a legal personality, but a term that comprises the above-mentioned: primary healthcare provided through grouped health centres integrated into the five regional health administrations (public institutes) and eight first-generation local health units (public corporate entities); and secondary health care, through hospitals, hospital centres, first-generation local health units, oncology institutes, among others (mostly public corporate entities, but also some public institutes).

This sector has been the subject of several reforms (Nunes, 2024), the latest resulting in the reorganisation of primary, secondary, and tertiary healthcare, as of 1st January 2024, provided through 39 second-generation local health units (public business entities) that replaced the remaining entities, and three oncology institutes (Lisbon, Coimbra, and Porto). It should be noted that the regional health services of the Azores and Madeira are not part of the NHS but depend on the respective regional governments within the scope of their autonomy.

The NHS faces several risks and challenges related to the ageing of the population it serves, and their comorbidity, increasingly complex diseases, particularly oncological ones, the introduction of innovative medication, diagnostics, and equipment, with impacts on its funding needs. There is also a management problem that the above integration has sought to address by increasing the size and breadth of the services provided through the 39 second-generation local health units to gain efficiency, better integration, and management of resources (Nunes, 2024). There are also problems arising from the various careers and their respective aspirations, conflicts, conflicting political doctrines about the path and sustainability of the NHS. The inability to resolve waiting lists for hospital appointments and surgery in time also has its tolls (Nunes, 2024).

There are other structural problems such as the excessive use of emergency services by the population – and the delay it ends up causing due to resources allocation – and the impact of COVID-19 pandemic due to the reorganisation of professionals and resources to deal with it, leaving many users with worsening medical conditions (Goiana-da-Silva *et al.*, 2024).

The NHS in numbers can be represented by the values shown in Table 1 that shows some numbers on the overall activity carried out in the NHS in 2022, showing the variation with 2021, showing negative variations in red and positive variations in green, depending on the polarity of the indicator (the higher the better, or, the lower the better).

Table 1. NHS key statistics

Global healthcare activity	2022 (in thousands)	Variation 2022/2021
Primary Health Care		
Patients without a family doctor	1494.4	31.2%
Medical consultations	34.5	-4.1%
Nursing appointments	18.4	-27.5%
Hospital Healthcare		
Medical consultations	12771.0	2.9%

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Table 1. Continued

Global healthcare activity	2022 (in thousands)	Variation 2022/2021
Surgical interventions	758.0	6.9%
Emergency episodes	6237.0	20.0%
Day hospital sessions	1455.0	10.4%
Elective hospital waiting lists		
First consultant appointment	583.0	11.1%
First consultant appointment in adequate time	68.4%	-11.5%
Surgery	235.0	6.8%
Surgeries performed in adequate time	69.4%	-1.7%

Source: Adapted from CFP (2023).

It should also be noted that Portugal has the second highest private health expenditure per capita of the OECD countries, which considers private insurance and out-of-pocket payments, despite NHS expenditure in 2022 being over 13 billion euros, which corresponds to 5.5% of GDP, 12.3% of public expenditure and a deficit of 1066.6 million euros (CFP, 2023), due to its chronic underfunding.

It is important for public services to be ever closer to their users, beneficiaries and taxpayers to get to know their aspirations, needs, problems and, in general, the limitations and obstacles they encounter in their journey through the ecosystem of NHS healthcare providers (Abidova *et al.*, 2020; Saraiva *et al.*, 2023).

It should also be noted that Portugal has the second highest private health expenditure per capita of the OECD countries, which takes into account private insurance and out-of-pocket payments, despite NHS expenditure in 2022 being over 13 billion euros, which corresponds to 5.5% of GDP, 12.3% of public expenditure and a deficit of 1066.6 million euros (CFP, 2023), due to its chronic underfunding.

It is important for public services to be ever closer to their users, beneficiaries and taxpayers to get to know their aspirations, needs, problems and, in general, the limitations and obstacles they encounter in their journey through the ecosystem of NHS healthcare providers (Abidova *et al.*, 2020; Saraiva *et al.*, 2023). Sentiment analysis enables the integration of user insights derived from their reactions to topics and posts over time, enabling the study of behavioural patterns (Abdukhamidov *et al.*, 2022).

Given the above, this study aims to understand public perceptions and emotions, which can lead to more effective policy-making and improved health services expressed through social media.

2. LITERATURE REVIEW

2.1. Sentiment Analysis

Sentiment analysis, as a text mining process, enables to extract information and insights from the general public that uses social networks and other similar platforms to comment, communicate opinion and express themselves (Ahmed *et al.*, 2022).

The mass use of images that mimic expressions and states of mind, such as emojis, limits the use of traditional text-based sentiment analysis algorithms, which are unable to interpret them (Al-Tameemi *et al.*, 2024), generating evolution for multimodal sentiment analysis.

Social media have become the biggest platforms where people express their opinions and emotions, at the same time misinformation and fake news are rife, a challenge to filtering, codifying, and understanding sentiments (Dumka *et al.*, 2022).

Bots, programmes with fake social media accounts that simulate human interaction with the aim of disinforming, present challenges to sentiment analysis (Kumar *et al.*, 2024).

Although disinformation is rife on social media, they are also critical for disseminating timely and accurate information and real-time feedback (Zaidi *et al.*, 2023).

Automated sentiment analysis is critical for recognising feelings in contrast to other sources of information and, today, can be obtained cost-effectively and comprehensively via the Internet. It is highly dispersed, disorganised and massified on countless platforms. Sentiment analysis thus makes it possible to deal with what. The ever-increasing availability of emotional data on social media can help to better personalise the goods and services produced, or political choices, with the ability to predict and plan (Al-Tameemi *et al.*, 2023), even considering the ever-increasing restrictions on personal data processing, making comments, likes and other shares are huge opportunities for research and operations management.

Murray *et al.* (2022) points out that surveys are a very structured source for obtaining opinion data and free text does not have this structure, which creates challenges, although through Natural language processing (NLP) it is possible to discover this latent structure, but these tools are usually applied by researchers with a technical background. It is therefore necessary to create or adapt a specific framework. Anta *et al.* (2022) highlight that this approach allows for the inclusion of individuals who would not otherwise fill out questionnaires and surveys.

Dumka *et al.* (2022) explain that the random nature of the text prevents computer systems from processing it, although data normalization makes it possible to reduce its randomness closer to standard models, improving efficiency.

Sentiment Analysis classifies the captured text into distinct categories, such as positive, negative and neutral, which helps recognise feelings (Agrawal *et al.*, 2022).

Irony, and even the more aggressive sarcasm, is a rhetorical resource widely used on social media, particularly in criticism and derisive attitudes, which is difficult for humans to recognise and even more so for software. This situation has led to work being done to develop machine learning in this linguistic resource (Bouazizi *et al.*, 2016).

2.2. Sentiment Analysis in Healthcare

The use of data from social media in healthcare is still limited compared to other industries (Khine *et al.*, 2024). Khine *et al.* (2024) argues that contemporary works in the field of medicine are divided into lexicon-based and machine learning-based approaches.

The polarities considered when analysing sentiment in healthcare are positive vs negative, with reference to patient comments to determine the degree of satisfaction with various aspects. To this end, models are used to train extraction by theme, not all of which are equally successful in detecting the respective polarity. There are more traditional approaches, such as NLP-based software, or more advanced ones, such as Deep Learning Approaches (Roche *et al.*, 2024).

Public concerns about healthcare systems have increased dramatically, especially after the COVID-19 pandemic, which has led to a demand for user feedback and monitoring it on the main social media platforms (Usman *et al.*, 2024).

The social media interactions of healthcare users are based on individual experiences from those who are the best evaluators of the service according to their expectations, so they provide a unique perspective that can complement other sources of data that may be available (Murray *et al.*, 2022), particularly about more technical and clinical matters where patients do not have the level of literacy, knowledge and expertise to give an unbiased and accurate opinion.

Policymakers can benefit from sentiment analysis (Agrawal *et al.*, 2022) to improve or refine their actions in legislation and governance. Harvesting the perceptions of users or potential users of a healthcare service can be important in designing more integrated and efficient solutions. The following Table 2 summarises the recent sentiment analysis studies reviewed.

The methods used in sentiment analysis range from dictionary-based approaches, such as VADER, to advanced deep learning and NLP techniques. Identified methods include convolutional neural networks (CNN) and long short-term memory (LSTM) models using libraries like Keras. Supervised learning techniques, such as support vector machines (SVM), logistic regression (LR), multinomial Naive Bayes (MNB), and random forests (RF), are also common. Unsupervised methods like latent Dirichlet allocation (LDA) and clustering algorithms are also utilized. Tools like Text-Blob, Flair, Python packages such as KoNLPy, and the R programming

language are frequently employed. Manual and semi-supervised analyses and models like BERT also play a significant role in sentiment analysis.

Table 2. General information on recent sentiment analysis research (healthcare domain).

Authors	Theme/healthcare topics covered	Period studied	Data extraction platform	Sentiment labels	Word cloud focus?
Thakur (2023)	COVID-19 and Mpx	7th May 2022/3rd March 2023	Hydrator app; RapidMiner Studio	“positive”, “negative” or “neutral”	Yes
Roche <i>et al.</i> (2024)	Pharmacovigilance focus on Levothyrox	2000/2020	Fasttext algorithm, FastText library	“positive” or “negative”	Yes
Dumka <i>et al.</i> (2022)	COVID-19	12th/30th March 2020	Kaggle	“positive”, “negative” or “neutral”	Yes
Anta <i>et al.</i> (2022)	Electroconvulsive therapy	1st January 2019/31th October 2020	Tweet Binder	“positive” or “negative”	
Lee <i>et al.</i> (2023)	dietary supplement consumer perceptions and trends (before and after COVID-19)	1st January/31th December 2019” (pré-COVID); 1st January/31th December 2021 (pós-COVID)	TEXTOM	“positive” or “negative”	
Kang <i>et al.</i> (2022)	Telemedicine after the COVID-19 outbreak	1st January 2019/1st March 2020 (pré-COVID); 2nd March/30th September 2020 (pós-COVID)		“positive”, “negative” or “neutral”	
Agrawal <i>et al.</i> (2022)	Vaccines, post-COVID-19 health issues and healthcare service providers	11th/25th May 2021	Twitter API, Python Library Tweepy	“positive”, “negative” or “neutral”	Yes
Rajkhowa <i>et al.</i> (2023)	Monkeypox vaccination	1st May/23th September 2022	Pandas Library	“positive”, “negative” or “neutral”	
Alathur <i>et al.</i> (2022)	Metaphorical content on e-participation in healthcare	April/June 2021	API	“positive”, “negative”, “trust”, “fear”, “anticipation”, “sadness”, “joy”, “anger”, Surprise” or “disgust”	Yes

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Table 2. Continued

Authors	Theme/healthcare topics covered	Period studied	Data extraction platform	Sentiment labels	Word cloud focus?
Zhu <i>et al.</i> (2024)	Patient perception and outcomes with Presbyopia-correcting intraocular lens (PCIOL)	September 2020/ October 2022	Python (Beautiful Soup) and manually	“positive”, “negative”, “neutral” or “mixed”	
Ruiz-Núñez <i>et al.</i> (2023)	Role of healthcare professionals in the global conversation during the AstraZeneca vaccine suspension	7th/23th March 2021; 7th/23th April 2021	AcademictwitterR library, Twitter API, software R - Rstudio (now called Posit)	“positive” or “negative”	
Schellack <i>et al.</i> (2022)	Social media reports and utilization for three re-purposed medicines: hydroxychloroquine (HCQ), ivermectin and colchicine	January 2020/June 2021	IQVIA	“positive” or “negative”	
Abrams <i>et al.</i> (2023)	Mental health and burnout in the health care workforce	January 2020/ November 2021	Quorum Analytics	“Democratic” or “Republican”	Yes
Khine <i>et al.</i> (2024)	Word embedding model integrated with medical knowledge for deep learning-based sentiment classification	December 2019/ August 2020	GeForce GTX 1050 Ti GPU and TensorFlow	“positive”, “negative” or “neutral” in WebMD.com, Drugs.com and COVID-19 policies Twitter	
Usman <i>et al.</i> (2024)	Patients satisfaction	July 2021	Tweepy	“positive”, “negative” or “neutral”	Yes
Al-Hamid <i>et al.</i> (2024)	Motivations, effects and toxicity of novel synthetic opioids from the perspectives of tweeters.	October 2022/May 2023	NVivo 12 Pro	“positive”, “negative” or “neutral”	
Kumar <i>et al.</i> (2024)	Healthcare supply chain	1st March/15th April 2020 (US); 1st May/15th June 2021 (India)	Twitter API	“positive”, “negative” or “neutral”	Yes
Zaidi <i>et al.</i> (2023)	COVID-19 misinformation	1st March/21th August 2020	Twitter API	“positive”, “negative” or “neutral”	
Praveen <i>et al.</i> (2023)	Perceptions of healthcare researchers regarding ChatGPT	N/D		“positive”, “negative” or “neutral”	
Mathieson <i>et al.</i> (2022)	Gabapentinoid (medicine) harms	8th March/7th May 2021	Brand24	“positive”, “negative” or “neutral”	

Source: Own elaboration.

Notably, around 40.0% of the studies used a word cloud, 50.0% had positive sentiment, 31.3% negative and 18.8% neutral. Regarding the social media platform used, 78.9% of the total included at least Twitter and 63.2% of the total was based exclusively on Twitter, as presented in Appendix 1.

The application of sentiment analysis is especially important in the provision of public services and particularly in healthcare, which is currently dealing with fundamental problems despite the deficits in knowledge and health literacy, it is very important to constantly monitor the opinion of those who comment, not least as a way of making improvements to services, better adapting them to users' needs, or merely knowing when to communicate better or differently.

3. METHODOLOGY

As a natural language processing (NLP) technique, Sentiment Analysis makes it possible to analyse texts – particularly in bulk – and classify messages as positive, negative, or neutral. Considering the high volume of comments on social media, it is important to know and map the feelings of those who interact with a company or organisation, seeking to better understand their needs, expectations, desires, and other feelings. This process can contribute, for example, to improving a product or social service. However, it does have its challenges, considering that language presents phenomena that can jeopardise a linear semantic analysis: situations such as sarcasm can have a positive reading when sentiment is negative, or *vice versa*.

3.1. Data Source

Social media networks or platforms are applications that allow users to create profiles and, through them, participate in a process of interaction with those who produce content more passively or actively, the latter, for example, when making a comment or a like and interacting with other users. These applications are based on “Web 2.0”, which has made it possible to move from an internet of consumption to one of participation and production.

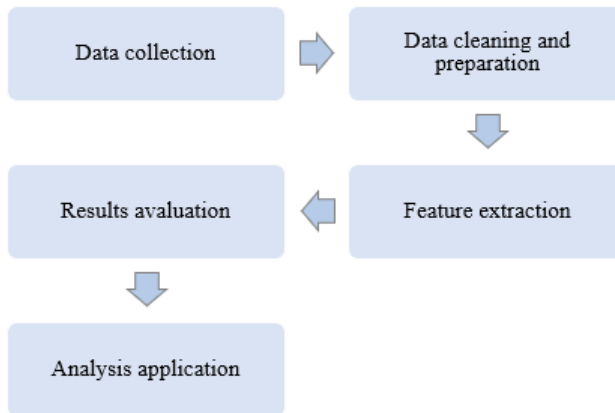
Facebook, YouTube, WhatsApp, WeChat, and Instagram are the social platforms with the most active users: over a billion. Out of the 8.7 million internet users in Portugal, 8.1 million are social media users, representing a usage rate of at least one social media platform of 92%, with females comprising 52% (Kemp, 2019).

Instagram has more than 2 billion users worldwide, 50,6% male. There are 5.3 million Instagram users in Portugal, 54.3% female, a add reach of 51.7% of its total population and a reduction of 100,000 users from 2023 compared to 2022 (Kemp, 2019).

Facebook has more than 3 billion users worldwide, 56,8% male. There are 5.9 million in Portugal, 52.1% female, an additional reach of 57.5% of its total population and a reduction of 50,000 users from 2023 compared to 2022 (Kemp, 2019).

Sentiment analysis requires work prior to data collection, from analysing what has been done by other researchers in this field, according to the literature review, followed by deciding on the methodology to be applied to data extraction and subsequent steps (El-Masri *et al.*, 2017), presented in Figure 1, which below is a detailed breakdown of each element of the flowchart.

Figure 1. Sentiment analysis methodology flowchart.



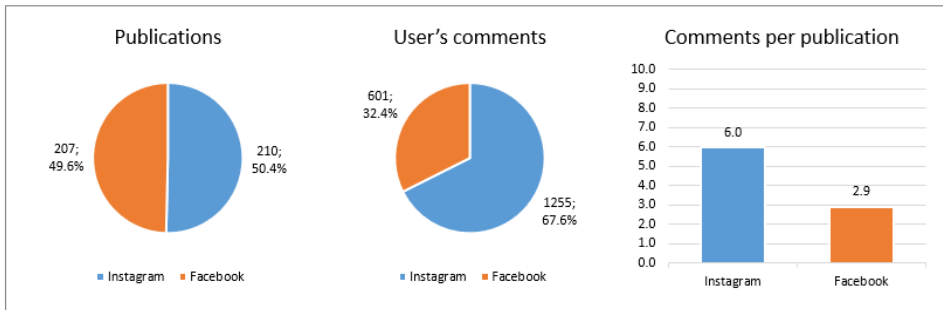
Source: Adapted from El-Masri *et al.* (2017: 54).

3.2. Data Collection

The data was collected from the official pages of the NHS on Instagram and Facebook over the same period, namely from September to December 2023. The official Instagram page of the NHS has 7,257 posts and 234,000 followers (https://www.instagram.com/sns_pt/), and the official Facebook of the NHS has 285,000 followers (<https://www.facebook.com/sns.gov.pt>).

An initial exploratory data collection was conducted between the 2nd and 3rd of March (2024), followed by a review of the data to complete contextual information necessary for enhanced understanding and classification, conducted between the 16th and 17th of March. The data collected is constituted by 417 publications and 1856 users's comments, as presented in Figure 2.

Figure 2. Posts, user’s comments and average per publication by platform.



Source: Own elaboration.

Figure 2 shows the number and percentage of posts and user comments per social media platform and the average number of comments per post during the period in question.

It is important to clarify that in the period considered (September to December 2023), the number and content of publications per day) that have the same meaning as post is the same. However, those without comments were not included, which explains why there were 210 posts from Instagram and only 207 from Facebook.

3.3. Data Cleaning and Preparation

After obtaining 44,427 words from the 1,856 comments on 418 posts, the data was cleaned and prepared in a process that required three stages. Thus, according to Table 3 below, stage 0 corresponds to the original data; stage 1 comprises the removal of emoji, and stage 2 removes punctuation, hashtags, numbers, and errors.

Table 3. Word count, data cleaning and preparation stages

Social media platform	# words			
	Stage 0	Stage 1	Stage 2	Stage 3
Instagram	28783	28385	28214	20330
Facebook	15644	15333	15008	10780
Totals	44427	43718	43222	31110
# of words eliminated by a subsequent stage		-709	-496	-12112
% of words eliminated by a subsequent stage		-1.6%	-1.1%	-28.0%
% of words eliminated compared to stage 0		-1.6%	-2.7%	-30.0%

Source: Own elaboration.

Stage 3 was composed of manually removing a few remaining emojis, special symbols, mention of users in comments, and redundant and meaningless words, totalling 31,110 words in the end, a reduction of 12,112 words (-30%) without losing meaning.

3.4. Sentiment Analytical Process

To analyse sentiment, the researcher needs data obtained by collecting user opinions through NLP, in this case from followers of the NHS pages on two social media platforms, and then applying another tool to classify and categorise them according to a specific topic.

The next two points below develop the components of this process of obtaining the data itself. The first consists of extracting the information inherent in the data, be it content, keywords, opinions and, in general, the elements indicating feelings that can be extracted and that the researcher considers relevant to the objectives and context that has been previously defined. The second consists of the classification, which is dichotomous, as in the case under study, into positive and negative elements. However, there may be more classifications which are described below, and which were used.

Feature Extraction

One method for reducing dimensionality involves feature extraction, which entails transforming outputs in such a way as to retain and preserve relevant information, thereby enhancing comprehension and estimation capabilities. This process involves condensing text by eliminating redundancy or irrelevance (Khalid *et al.*, 2014).

Valence

Given the primary objective of this study to delve into sentiment analysis rather than deep learning models, an *ad hoc* valence approach was employed. This involved meticulous scrutiny of the comments to discern their sentiment, categorizing them into distinct “Positive” and “Negative” classifications. Additionally, to accommodate the diverse and nuanced nature of the comments, two supplementary categories, namely “Neutral” and “Mixed”, were introduced. This tailored methodology was deemed essential to effectively capture the sentiment spectrum inherent in the open-ended data.

To obtain the value associated with the sentiment, automatically, the Orange Data Mining software was used, where the VADER algorithm was applied to obtain the result in the form of the sentiment value (Hutto & Gilbert, 2014). The result

obtained using the VADER algorithm is a value between -1 and +1, representing the most negative and most positive sentiment respectively, and is returned to the libraries available online (Hutto & Gilbert, 2014).

3.5. Hypotheses

Between the first exploratory data collection and the complete review, a process described in point 3.1 above, the following hypotheses were formulated, which, together with the study's objectives, would allow the research to be framed and help interpret and discuss the results and, above all, would serve to contribute to scientific knowledge and provide clues as to the main policy implications and impacts on practice.

Hypothesis 1: *The public opinion's perception of the Portuguese National Health Service is positive.*

Hypothesis 2: *There is no difference in the public's perception of the Portuguese National Health Service according to gender.*

Hypothesis 3: *There is no difference in the public's perception of the Portuguese National Health Service according to social media comments.*

4. RESULTS AND DISCUSSION

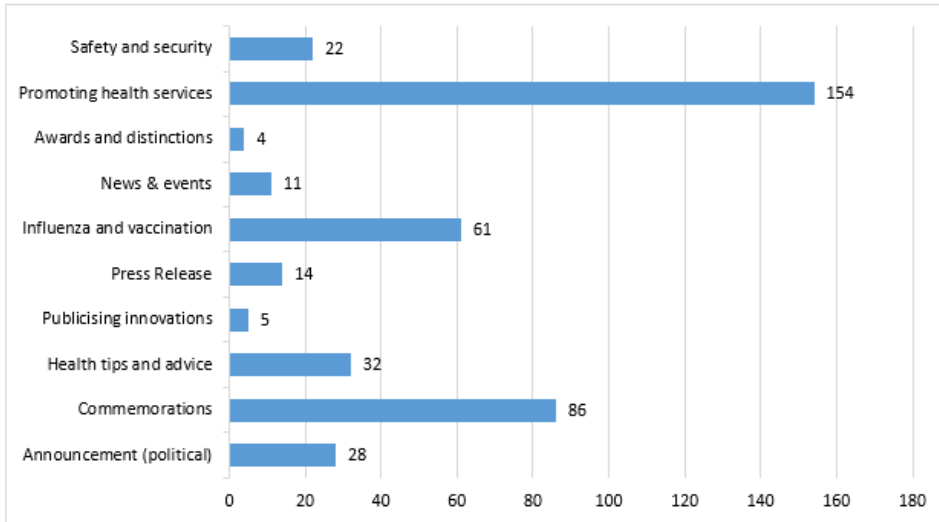
4.1. General Description

This chapter describes the results and identifies the statistically relevant patterns detected in the studied dimensions.

Again, it is important to point out that the two NHS pages have precisely the same number of posts. Hence, the differences expressed below result from the extraction criterion being posts with comments, thus explaining that the differences between social media are only due to the greater or lesser (or non-existent) number of comments.

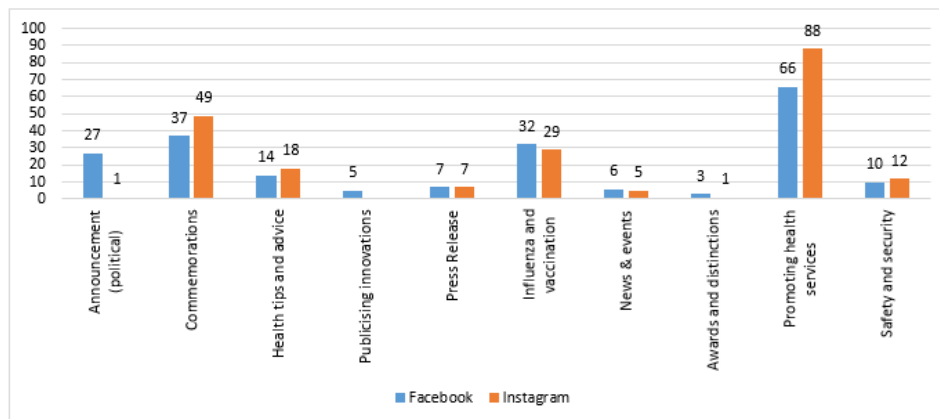
Based on a classification of posts by type, “Promoting health services” was the most expressive, with 37% of the total. This was followed by “Commemorations” and “Influenza and vaccination”, with 20% and 15%, respectively. Overall – and with a few exceptions – the findings described in Figure 3 follow the same pattern, regardless of the social media platform, as seen in Figure 4.

Figure 3. Number of posts by type



Source: Own elaboration.

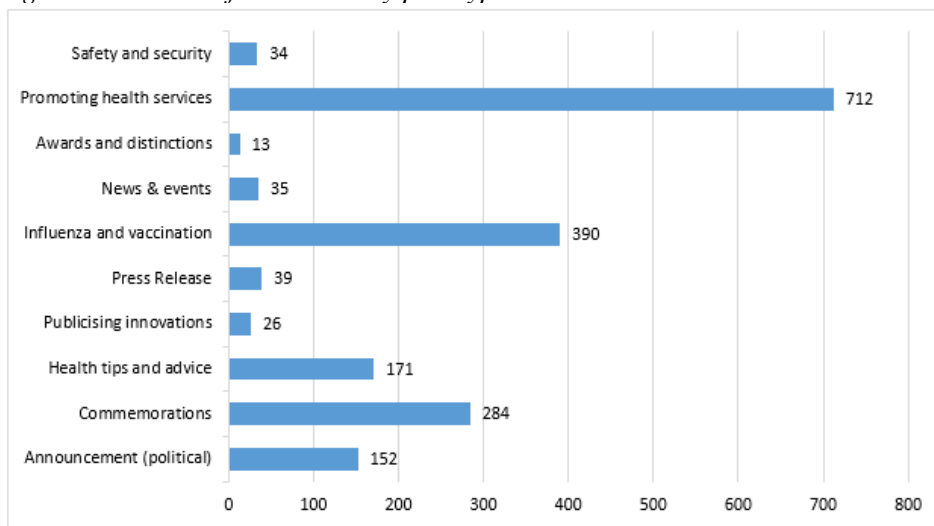
Figure 4. Number of posts by type and social media platform.



Source: Own elaboration.

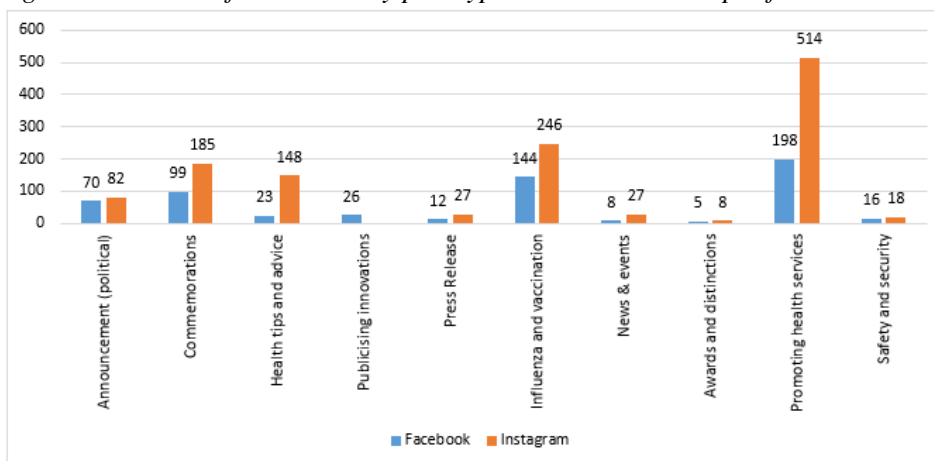
“Promoting health services” was the most commented topic (post), with 38%. This was followed by “Influenza and vaccination”, with 21%, and “Commemorations”, with 15%. The other types, as in the previous analysis by several publications, show frequencies of only one digit.

Figure 5. Number of comments by post type.



Source: Own elaboration.

Figure 6. Number of comments by post type and social media platform



Source: Own elaboration.

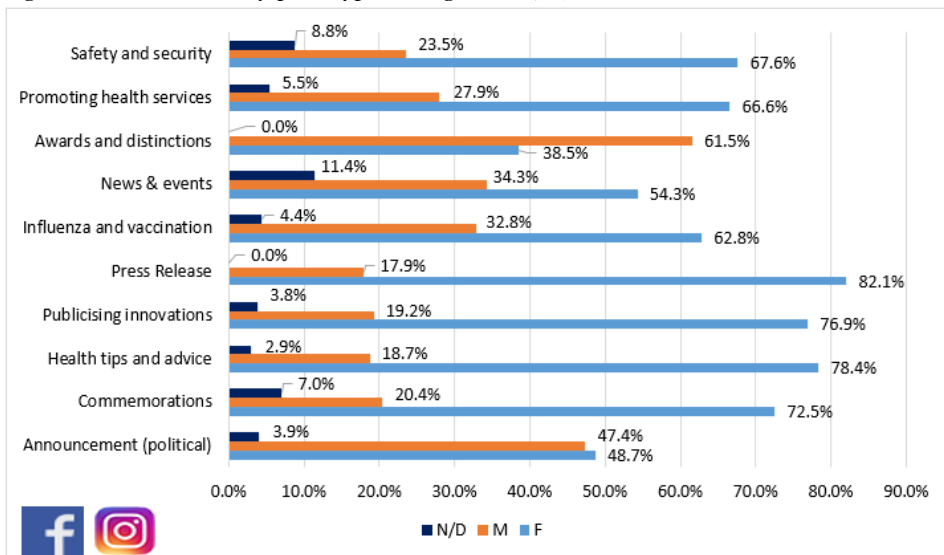
Also, in comments by post type and social media, there is overall homogeneity in the distribution of frequencies by platform.

4.2. Description by Gender

It is important to characterise comments by gender, as this can help decision-makers in the actions and campaigns they can develop to improve their presence on social media and the clarity and efficiency of their intervention, as presented in Figure 7.

Around 66% of the comments are female and 29% male, with 5% undetermined. Male comments only outnumber females in the “Awards and distinctions” category, regardless of the social media platform. In the others, the proportion of females is much higher.

Figure 7. Comments by post type and gender (%).



Source: Own elaboration.

There is also an uneven and rather disparate distribution of comment types, with the most significant being “Press Release”, with 82% female and 18% male, followed by “Health tips and advice”, “Publicising innovations”, “Commemorations”, “Safety and security” and “Promoting health services”.

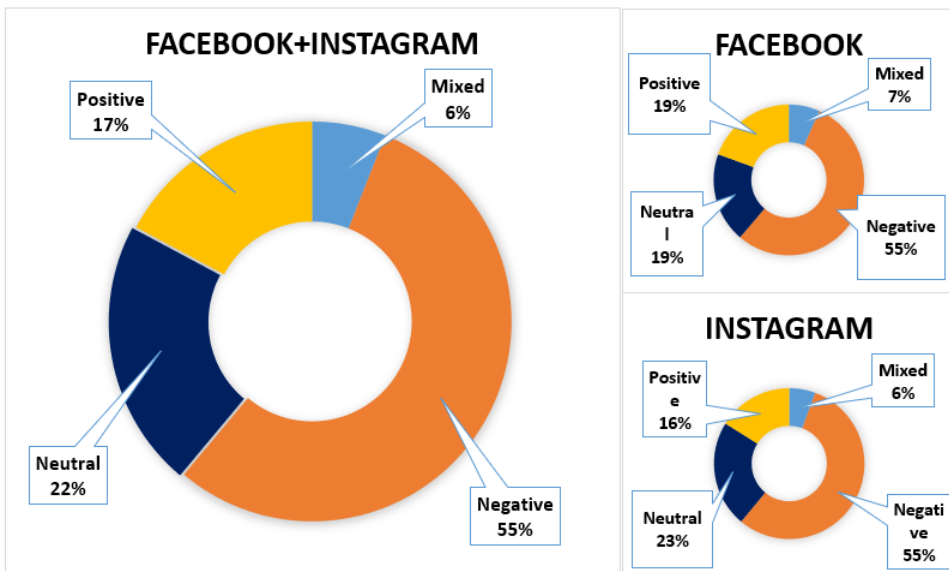
4.3. Description by Label

To better capture the sentiments, present in user comments during the period in question, sentiment categories were created and labelled. These sentiments are also characterised by gender and social media platform.

Figure 8 shows that the comments per “label” are in general negative, with a proportion of 55%. The remaining 45% are divided between comments with no expression of sentiment, labelled as “Neutral” (22%), positive comments (17%) and mixed comments (6%), which combine positive and negative sentiments in the same comment.

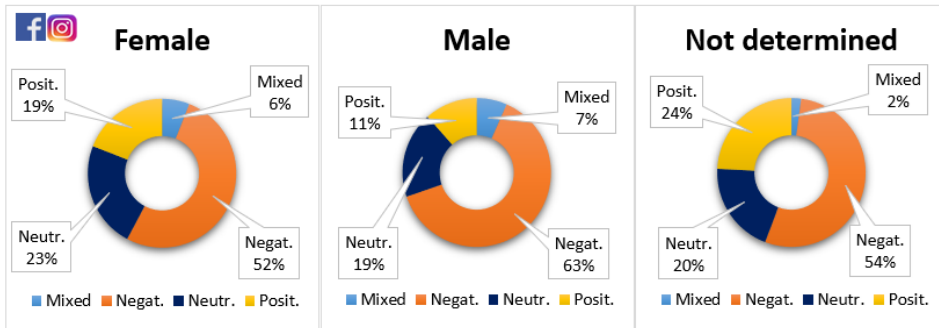
By gender, the proportion of negative comments is lower for women (52%) than for men (63%). The proportion of positive comments is 19% for women and only 11% for men. As we will see below, these sentiments do not differ (greatly) depending on the social network analysed.

Figure 8. Comments by label (%)



Source: Own elaboration.

Figure 9. Instagram and Facebook comments by gender and label (%).



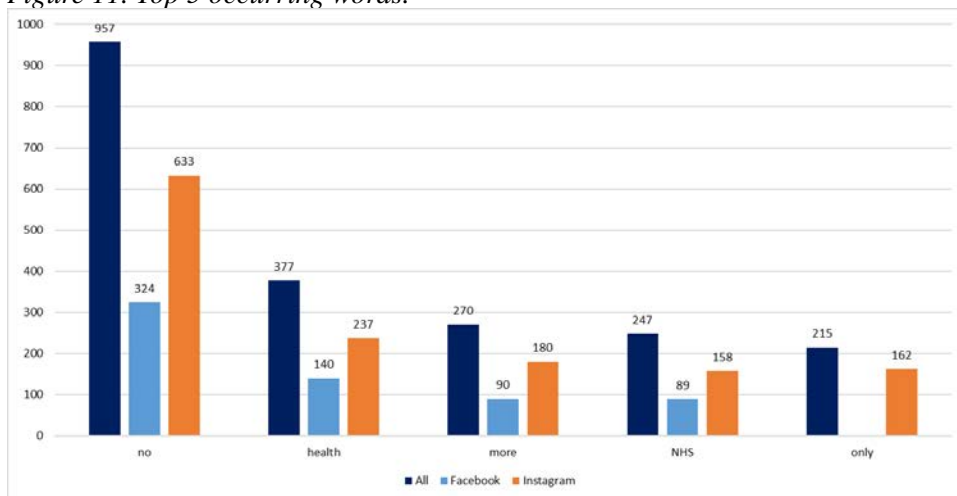
Source: Own elaboration.

4.4. Description by Word Cloud

Trends can be analysed using word clouds. This is a way of extracting critical information, which can be relevant because of the context it provides, through visual effects that simplify it, much like the previous figures, although in this case, through specific software that, based on their count, organises the words, particularly in size, according to the frequency with which they appear.

The following Figure 10 shows a group of word clouds. There is a general representation, centred and above, and just below, representations of the count by female and male gender.

Figure 11. Top 5 occurring words.



Source: Own elaboration.

4.5. Discussion

Based on the results, it is important to return to the initially formulated hypotheses that helped guide this research process:

As Hypothesis 1, the public opinion's perception of the Portuguese National Health Service is positive: With a negative comment rate of 55.1% and a positive comment rate of 17.2% (23% neutral and 6% mixed; $n=1,856$ comments), hypothesis 1 should be rejected.

As Hypothesis 2, there is no difference in the public's perception of the Portuguese National Health Service according to gender: Considering that there are comments with unclassified gender, only those where it was possible to ascertain were considered ($n=1,761$ comments).

Despite following the same trend in the ratio of negative to positive comments, the proportion differs, with males having 63.1% of negative comments and females 51.8%. On the other hand, it is the female gender that has the most positive comments (19.1%) and the male gender the least (11.5%). Hypothesis 2 should be rejected.

As Hypothesis 3, there is no difference in the public's perception of the Portuguese National Health Service according to social media comments: Comments ($n=1,856$) originating from Instagram and Facebook have a similar negative proportion (55%), differing slightly in terms of positivity, with a difference of 3.4 percentage points on Facebook (19.5%) compared to Instagram (16.1%), which is not statistically signif-

icant in capturing sentiment through this particular method of sentiment analysis. Hypothesis 3 should not be rejected.

The results of the study indicate that the predominant negative sentiment towards the Portuguese National Health Service (NHS) is strongly linked to structural and operational issues, such as long waiting times for appointments and surgeries, chronic underfunding, and difficulties in accessing primary care, evidenced by the high number of patients without a family doctor (a 31.2% increase in 2022). Additionally, recurring patterns in complaints include dissatisfaction with the organization of emergency services, which are frequently overwhelmed due to overuse by the public, and the lack of institutional engagement on social media, where critical comments receive no interaction or clarification. The contextual analysis reveals that these issues are exacerbated by factors such as an ageing population and shortages of human resources, particularly in medical specialities. This context adds significant value to the study, as it not only identifies the causes of negative sentiment but also highlights priority areas for intervention, such as improving institutional communication and optimizing resource allocation, which could be decisive in reversing public perception.

The literature review highlighted key challenges in sentiment analysis, such as the difficulty of interpreting sarcasm, and unstructured text, issues that directly informed the study's methodology. To address these, the research employed a multi-stage data cleaning process (removing emojis, punctuation, and redundant words) and a manual valence-based classification system, categorizing comments as positive, negative, neutral, or mixed. This approach aligned with recent studies (e.g., Al-Tameemi *et al.*, 2024; Dumka *et al.*, 2022), which emphasize the need for tailored frameworks to handle noisy social media data. The results validated these methodological choices, revealing a high proportion of negative sentiment (55.1%), with patterns mirroring broader healthcare sentiment research (e.g., Usman *et al.*, 2024), where systemic inefficiencies dominate complaints. By grounding the methodology in literature-derived challenges, the study ensured robust handling of linguistic nuances, reinforcing the reliability of its findings.

Furthermore, the literature review underscored the value of social media as a real-time feedback tool for public services (Abidova *et al.*, 2020; Saraiva *et al.*, 2023), a premise tested through the study's focus on NHS Instagram and Facebook interactions. The methodology's design—tracking post types (e.g., “Promoting health services”) and user demographics—directly operationalized this insight, revealing gendered disparities in sentiment (e.g., 63.1% negative among males vs. 51.8% among females). These results not only corroborate prior findings on healthcare communication gaps (Simões & Fronteira, 2021) but also extend them by quantifying platform-specific trends (e.g., homogeneous negativity across Instagram and Facebook). Thus, the study bridges theoretical frameworks from the

literature with empirical methodology, demonstrating how sentiment analysis can translate into actionable policy insights, such as the need for proactive institutional engagement on social media.

5. CONCLUSIONS

In this research, the perception of public opinion of the Portuguese National Health Service was determined by sentiment analysis based on user interaction with the official NHS Instagram and Facebook pages.

The results show a tendency towards mostly negative sentiment, regardless of the social media platform or gender of users, with an overall negative comment rate of 55.1% to a positive rate of only 17.7%, which presents a high reputational risk.

Considering this conclusion as an actionable recommendation for policymakers, it is suggested that the NHS's presence on social media platforms and communication strategies be reviewed. Analysing the 1,856 comments, 1,023 of which were negative and 111 mixed (so partially negative), showed no institutional presence in the comment boxes, which were limited to posting the publications. Even in situations of blatant user attempts at disinformation, inappropriate content, cyberbullying, dissemination of fake news or, on the other hand, requests for simple and non-technical healthcare guidance that could be actively answered, there was no interaction.

As such, a policy implication could be a more active, persistent, and permanent mediation through comments, which allows for better guidance and even clarification for users who comment or just read, which helps with the experience and promotes an improvement in the perception of the NHS and citizen engagement, throughout social media.

Considering the low cost and availability of data, it is also recommended that the NHS systematically and persistently use sentiment analysis to monitor the opinions of its social media users to improve its communication and even fine-tune (or pre-test) certain policies, measures, and actions, considering that real-time feedback is available.

Some limitations to the research include the subjectivity inherent in the data and, considering the method used, the researcher's potential bias or inability to detect nuances. The exclusion of symbols such as emojis removes some comments (and context) of users who only communicated with this form of comment, which could provide more detail if converted into text and labelled in terms of sentiment. Finally, the sample could be larger by increasing the number of months considered and focusing on just one of the platforms.

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