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Gender inequality on Twitter during the UK election of 2019

La desigualtat de gènere en Twitter durant les eleccions britàniques de 2019

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Resum: Actualment, les plataformes de xarxes socials com Twitter tenen un paper essencial en la política i els moviments socials. L'objectiu d'aquest article és comparar i contrastar el llenguatge utilitzat a Twitter per referir-se als candidats de les darreres eleccions generals del Regne Unit de desembre de 2019 per tal de crear consciència sobre la desigualtat de gènere a la política. La metodologia seguida es basa en tres aspectes: (a) un anàlisi quantitatiu mitjançant Sketch Engine per extreure les principals colocacions del corpus; (b) un anàlisi del sentiment dels tuits compilats mitjançant dues classificacions de lèxic: BING (Hu i Liu, 2004) i NRC (Mohammad i Turney, 2013), que classifica les paraules en vuit emocions bàsiques i dos sentiments (positiu i negatiu)); i (c) un anàlisi qualitatiu que utilitza un enfocament d'Anàlisi Crític del Discurs (Fairclough, 2013) per examinar l'abús verbal envers les dones des d'una perspectiva lingüística.
Paraules clau: corpus; anàlisis del sentiment; discurs de l'odi; dones; Twitter.

Abstract: Social media platforms such as Twitter play an essential role in politics and social movements nowadays. The aim of this paper is to compare and contrast the language used on Twitter to refer to the candidates of the last UK general election of December 2019 in order to raise awareness of gender inequality in politics. The methodology followed is based on three aspects: (a) a quantitative analysis using Sketch Engine to extract the main collocates from the corpus; (b) a sentiment analysis of the compiled tweets by means of two lexicon classifications: BING (Hu & Liu, 2004) and NRC (Mohammad & Turney, 2013), which classifies words into eight basic emotions and two sentiments (positive and negative); and (c) a qualitative analysis employing a Critical Discourse Analysis approach (Fairclough, 2013) to examine verbal abuse towards women from a linguistics perspective.
Keywords: corpus; sentiment analysis; hatred speech; women; Twitter.

1. Introduction

The last UK general election of December 2019 was marked by Brexit. The Conservative Party won and strengthened its position on Brexit, securing a mandate to ensure the UK's departure from the EU on January 31st, 2020. Labour's defeat led to the resignation of its leader Jeremy Corbyn. Jo Swinson, leader of the Liberal Democrats, lost her constituency seat, which also forced her departure. And the Scottish National Party (SNP) success led to renewed calls for a second independence referendum.

Social media platforms such as Twitter play an essential role in politics and social movements nowadays (Kuperberg, 2021). Twitter has more than 300 million users worldwide, who post around 500 million tweets/day, so it has become highly useful for a better understanding of people's opinions, feelings, and emotions. According to Twitter, more than 15 million tweets were posted about the election from November 6th to December 12th 2019, highlighting how political discourse continues to thrive on the platform. Unfortunately, social media platforms have also become a new space to express violence against politicians, turning into a new continuum between online and offline spaces (Esposito, 2021).

Women in politics (WIP, henceforth) have historically been underrepresented but their proportion has increased over time. In January 2021, there were 10 women serving as Head of State and 13 serving as Head of Government. Particularly celebrated are the cases of the Central African state of Rwanda, which has the highest representation of women MPs (61%) in the world, and Cuba (53%), which also has female majority in parliament. In the European Parliament, 41% of European MPs are women, and in the UK, there are 220 women MPs in the House of Commons (34%), an all-time high (Watson et al., 2021). However, politics remains highly dominated by men, and as shown in a recent survey on women MPs in Europe (Inter-Parliamentary Union, 2018), WIP have to face acts of sexism, harassment, and violence, which prevents parliaments from being inclusive and democratic.

The day after the election we saw a statement from Baroness Brinton (previous president of the Liberal Democrats) saying that Jo Swinson had faced misogyny during the campaign: "She [Swinson] has been on the receiving end of an enormous number of comments which male politicians don't face[1]".

[1] Jo Swinson tripped to lose her seat after disastrous campaign for Lib Dem leader. https://www.mirror.co.uk/news/politics/jo-swinson-tipped-lose-seat-21086680 [Accessed: 01/05/2021]

When comparing men's and women's experiences of violence in politics, men are more often victims of physical violence, and women are more likely to face psychological violence (Bardall, 2011). Some scholars believe that it is essential to analyse men and women together to discern whether gender plays a role in violence against political actors (Bjarnegård, 2018). Inspired by Baroness Brinton's statement about Jo Swinson, in this paper we will compare the language used on Twitter to refer to both men and women candidates of the last UK general election in order to examine if gender was relevant in abusive tweets.

This paper is organised as follows. Section 2 offers a review of the literature on gender, politics, and violence, as well as a collection of recent studies on verbal abuse against WIP on Twitter. Section 3 describes the data and methods followed in this paper. It contains the procedure of analysis, corpus description, and analytical framework. Section 4 presents and discusses the results in two sections: corpus-based analysis and lexicon-based sentiment analysis. Finally, in section 5 conclusions are drawn on gender inequality on Twitter during the UK elections of 2019.

2. Gender, politics, and violence

WIP are constantly judged about their public and private lives, which leads to the judgment of their public performance: "for a woman to seek and hold power is strange, marking her as unfeminine and dangerous. This belief allows culture to exclude women from full participation in any of its politics" (Lakoff, 2003: 161). A good example of this is Hillary Clinton and the scandal of Monica Lewinsky. It is shocking how it was mostly women who criticised her fitness for being a senator because she did not end her marriage. At that time, few women achieved important positions in politics or anywhere outside home and, if they did, they needed to be careful not to be tagged as "unfeminine" but, at the same time, behave in a similar manner as the men who occupied such positions (Fairclough, 2015: 187-8). Margaret Thatcher had to face this dilemma in a conservative party in which men surrounded her. However, Fairclough believes that she managed to create an image of herself as a feminine political leader thanks to a great deal of work and good advice on her voice and look.

Gender-based violence against political actors, commonly labelled "Violence Against Women in Politics" (VAWIP) (Krook, 2020), can be physical, sexual, psychological, economic, and semiotic (Krook & Restrepo Sanín, 2019). Semiotic violence, which involves the use of text and images, is becoming an increasingly mainstream phenomenon (Esposito, 2021: 2). However, Esposito argues that this new trend is not a simple consequence of social media and its affordances, as they are mere facilitators and replicators of "pre-existing hierarchical gender and power relations" (Esposito, 2021: 2). For instance, the anonymity offered by social media facilitates users to verbally abuse politicians and public figures. While some of these abusive comments are reported and deleted by platforms, most of them are public and get to the target.

Semiotic violence "is less about attacking particular women directly than about shaping public perceptions about the validity of women's political participation more broadly" (Krook, 2020: 187). Kuperberg (2021) identifies two practices of semiotic VAWIP: making women incompetent and making women invisible. This can be done through different strategies such as objectifying women, emphasising physical appearance, and describing them as bad mothers or failed women with the aim of emphasising men as the "only legitimate participants" of the political sphere (Krook, 2020: 190).

Previous studies on VAWIP examine the "cost of doing politics" (Krook & Restrepo Sanín, 2019). They develop an empirical approach for identifying cases of VAWIP, which consists of six criteria to establish whether gender bias was the motivation of an attack to then apply this framework to analyse three cases: the assassination of Benazir Bhutto, the impeachment of Dilma Rousseff, and the murder of Jo Cox. Georgalidou (2017) examines abusive language and sexism towards women MPs in the Greek parliament. Even though confrontation is expected in political discourse, Georgalidou's analysis reveals that the discourse addressed to women MPs is aggressive and contains language choices which are aimed at hurting another person, delegitimising women as political actors and shifting the interest from debating political agendas.

Some researchers have recently studied verbal abuse against WIP on Twitter. Fuchs & Schäfer (2020) highlight that misogynist forms of verbal abuse towards women on social media, and WIP in particular, have received less attention in existing research, and thus, they present an explorative analysis of instances of misogynist or sexist hate speech and abusive language against four Japanese female politicians on Twitter. Pérez-Arredondo & Graells-Garrido (2021) explore the linguistic and discursive patterns of verbal abuse against pro-choice WIP in Chile. Apart from tweets containing sexual, physical, and psychological threats, they encountered that women were also targeted as unsuitable to continue with their jobs because they had tolerated and protected a crime.

Other proposals take action against verbal abuse on Twitter. Ahluwalia et al. (2018) present a machine learning model for the detection of misogyny on Twitter. Similarly, the proposal by Plaza-del-Arco et al. (2020) detects misogyny and racism in Spanish tweets. In the political arena, Cuthbertson et al. (2019) introduce ParityBOT, a Twitter bot that counters abusive tweets aimed at women in politics by sending supportive tweets about influential female leaders. These projects aim to counteract hate speech against women on social media and to fight for gender equality.

3. Data and methods

3.1 *Procedure of analysis*

This paper explores the difference in the language used to describe men and women candidates in the 2019 UK elections. The research question we aim to answer is the following: is there a difference in both degree and manner in the way Twitter users criticise political candidates according to their gender? With that in mind, the methodology followed is based on four main steps: data collection, data cleaning, quantitative and qualitative analysis. We started by downloading the tweets we needed using Twitter's API. It allows the user to search for keywords and hashtags, and it also has other useful parameters which permit to filter your search by language, top tweets, or specific users. Due to the large amount of data related to the general election on Twitter, we chose the BBC Question Time debate (#bbcqt) as our sample, the only debate to include the main party leaders: Sturgeon, Swinson, Johnson, and Corbyn (see 3.2. Corpus description).

Before starting with the analysis, the tweets obtained from Twitter's API required a cleaning process through regular expressions in order to delete irrelevant information to our study. Data cleaning was an arduous but essential task when working with a large volume of data since it allowed us to remove the *noise* we found in our corpus: retweets, hashtags, handles, URLs, tabs, blank spaces, etc. We also found out that, even though we specifically downloaded tweets in English, our corpus contained tweets in other languages that we needed to reject.

Once the data was cleaned, we started with the quantitative analysis using Sketch Engine (Kilgariff et al., 2014), a user-friendly corpus tool which contains 500 ready-to-use corpora in more than ninety languages. Sketch Engine[2] is a highly useful tool for discourse analysts since they can explore their corpora and see what it "tells us about the attitudes, power relations and perspectives of the participants" (Kilgarriff et al., 2014: 15). In this research, as we want to compare the language used to refer to the candidates, we have used keywords and the word sketch, which processes the words collocates.

Then, the programming language R was used with a twofold objective: on the one hand, to enrich the aforementioned analysis with additional information; and on the other, to provide a wide range of graphics to display the results. R is a high-level programming language, and although it was created for statistical computing, it can also be used for linguistics (Desagulier, 2017). We analysed the evaluative language of the tweets using two lexicon classifications: BING (Hu & Liu, 2004) and NRC (Mohammad & Turney, 2013), which classifies words into eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two sentiments (negative and positive).

Finally, we carried out a qualitative analysis from a Critical Discourse Analysis (CDA) approach following Fairclough (2013). To this end, we used the concordance tool from Sketch Engine to closely analyse the words previously retrieved from word sketch and see the context in which they take place.

3.2 *Corpus description*

The first televised election debate took place in 1960 between John F. Kennedy and Richard Nixon with over 66 million viewers. It triggered a tremendous change in the history of debates, a new age in which candidates should master television to succeed. In contrast, it was not until 2010 that the UK broadcast the first televised debate between Gordon Brown (Labour and PM at the time), David Cameron (Conservatives), and Nick Clegg (Liberal Democrats).

According to Coleman (2000), televised debates are the best way of reaching a large audience of voters. Their contributions are numerous: they are the most-watched events in any campaign coverage and, thus, greatly impact vote decisions. Debates educate the audience to look for more information about the policies discussed and get to an informed decision about who to vote for. If, after a debate, the viewers are left questioning the policies and discussing them with friends and family, it means the debate has achieved its democrat-

[2] Sketch Engine: https://www.sketchengine.eu/ [Accessed 01/05/2021]

ic purpose. Televised debates also represent equality between the different political forces as they have the same opportunity to demonstrate to the audience why they should vote for them. It does not matter if they are candidates who have never held office or they are the current Prime Minister. The leader who is behind in the polls has the same opportunities as the one who is the potential winner. Moreover, televised debates create an illusionary intimacy between the audience and the candidate that no other medium can create.

Nowadays, in the Information Era, not only can we watch the debates on television but also comment on them in real time on social media platforms such as Twitter, a social networking service that was launched in 2006. Users interact with messages (tweets) restricted to 280 characters which are usually written in informal language. Due to the length limit, tweets are easier to analyse and thus, it is often easier to achieve high sentiment accuracy (Liu, 2012: 16).

For these reasons, we decided to compile a corpus of tweets from the BBC Question Time, a weekly program in which representatives of the most important parties discuss current political affairs. This debate, tweeted by the hashtag #bbcqt, took place on November 21st before the general election of December 12th 2019, and it was the only debate to include the main party leaders: Boris Johnson (Conservatives), Jeremy Corbyn (Labour), Nicola Sturgeon (SNP), and Jo Swinson (Liberal Democrats).

Our corpus consists of 106,999 tweets containing 2,514,936 words (see table 1). As expected, the current Prime Minister, Boris Johnson, and the opposition leader, Jeremy Corbyn, are the ones users tweeted the most about. Interestingly, even though our corpus contains a similar number of tweets from Johnson (41,529) and Corbyn (41,184), users tended to write longer posts when talking about Corbyn. Regarding the rest of the candidates, users tweeted more than twice about Jo Swinson (16,704) than Nicola Sturgeon (7,582).

Candidate	*Tweets*	*Words*
Boris Johnson	41,529	854,006
Jeremy Corbyn	41,184	1,113,396
Nicola Sturgeon	7,582	186,616
Jo Swinson	16,704	360,918
TOTAL	106,999	2,514,936

Table 1. Corpus size

3.3 *Analytical framework*

We follow corpus-assisted discourse studies (CADS) and sentiment analysis (SA) methodologies to examine the language used on Twitter to refer to the candidates of the last UK general elections. CADS combines both discourse analysis and corpus linguistics frameworks and it is defined by Baker (2006, 2010, 2020) as a computer-aided approach that analyses large amounts of electronic data comprised of written and/or spoken texts that are representative of a particular register. Similarly, Partington (2008, 3-5) defines CADS as the process needed to uncover "non-obvious meaning" based on the investigation and comparison of particular discourse types.

The main appeal of CADS lies in its ability to integrate close linguistic analyses with larger corpora analyses (Ancarno. 2020: 165). By combining corpus linguistics and discourse analysis, CADS applies quantitative and qualitative methods of text analysis. Quantitative data alone can reveal a lot about the underlying context. Simple text metrics such as frequency lists, type/token ratio, or keyword identification differentiate discourse and establish basic patterns. Qualitative analysis tools, such as concordancing and advanced search, help the researcher to quickly test hypotheses and identify language patterns.

Partington & Johnson (2020: 7-8) believe that the use of corpora adds value to the analysis of political language. Their distinction between the political language researcher and the activist researcher is interesting. While the political language researcher is only interested in the analysis of political language to uncover non-obvious ideological meanings, the activist's aim is political action and social change. Activists want their research to positively impact issues like social injustice, hatred, or abuse of minority groups. This paper aims not only to analyse the language used on Twitter to refer to the candidates, but also to make people aware of the gender inequality that is still present in our society, including the political scenario.

Sentiment analysis, also called opinion mining, is the analysis of "people's opinions, sentiments, evaluations, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes" (Liu, 2012: 7). The rise of sentiment analysis research is simultaneously linked with the growth of social media as there is a vast volume of opinion-based data ready to analyse. Opinions have an impact on our behaviour and our decisions; for this reason, they are essential when purchasing a new product, choosing a hotel, or voting in an election. According to Pang & Lee (2008: 8), applying SA to political opinion in social media is interesting as it shapes the user's vote intentions. Social media is accessible to everyone, and contrasting views between users are expected to be found. For instance, Twitter is utilised by most politicians, journalists, and other figures involved in the political scene, which makes it a rich source of information containing multiple references about campaigns, debates, elections, and daily news.

Sentiment analysis classifies texts according to their polarity (positive or negative), and it aims to identify "opinion-oriented language in order to distinguish it from objective language" (Pang & Lee, 2008: 9). There are two methods to achieve this objective. On the one hand, machine learning techniques, whether supervised or unsupervised, make use of a tagged dataset to train an algorithm. This algorithm is later assessed with another tagged dataset to compare the results and accuracy. Nowadays, most machine learning sentiment classifiers are based on neural networks. On the other hand, the lexical approach involves the use of rich lexical sources purposely annotated for sentiment analysis. The lexical method is based on a lexicon, that is, a list of the sentiment or opinion words in which the sentiment polarity of each item is indicated. Lexicons are like dictionaries, but words are assigned a polarity rather than a meaning (Moreno-Ortiz, 2017: 134). Those lexicons can be compiled either manually or automatically using seed words. The BING lexicon (Hu & Liu, 2004) and the NRC lexicon (Mohammad & Turney, 2013), which will be used in this paper to analyse the tweets, are two examples of lexicons created for sentiment analysis. Even though we believe in the usefulness of this approach, some researchers like Taboada et al. (2011: 270) or Mohammad & Bravo-Márquez (2017: 1) warn that, since it needs human decision taking, it can lead to annotation errors.

4. Results and discussion

4.1 *Corpus-based analysis*

One of the most typical techniques used in corpus linguistics to analyse a text is terminology extraction, also known as keywords (Baker, 2006). Keywords are extracted from a text by means of comparing the focus corpus to a reference corpus[3] to identify what is unique or typical. Single keyword extraction

[3] We used English Web 2020 (enTenTen20) as our reference corpus.

was problematic, since our corpus contains a significant sum of terms which are not describing the target candidates. For instance, we find hashtags related to the debate or the general election (*#bbquestiontime*, *#ge2019*, *#ge19*), other related to labour and tories (*#labourforhope*, *#toriesout*), and some abbreviations of the Scottish independence referendum (*indyref*) and Liberal Democrats (*libdem*). Regarding multiword keywords, results shed more light on candidates' descriptions. Table 2 is a selection of the top 50 multiword keywords in which we have filtered the most common ones dealing with the debate in particular and to general politics. Keywords extracted from Johnson's and Corbyn's subcorpora are related to their attitude towards politics and to their policies. Thus, some of them refer to Corbyn's alleged anti-Semitism, i.e. *terrorist sympathiser, anti semitism, anti semite* or *anti apartheid*. Additionally, there are words which make reference to their policies: *class war* or *free broadband*. On the other hand, and in the same vein, Johnson's keywords refer to the involvement of Russia in the Brexit process, i.e., *Russian interference* or *Russian report*, but also to his attitude, calling him a *liar* (*compulsive liar, serial liar* and words related such as *fact check*). In fact, some of the hashtags used were *#LiarJohnson* and *#JohnsonTheLiar*.

(1) Corbyn is an **anti Semitic**, **terrorist sympathiser** and Marxist.

(2) Boris Johnson didn't answer the question on **Russian interference**.

(3) Tell the truth for once if you know what that means Please. Boris Johnson is a **serial liar**.

Swinson	*Sturgeon*	*Johnson*	*Corbyn*
bedroom tax	*scottish independence*	*climate crisis*	*neutral stance*
nuclear button	*confirmatory referendum*	*russian interference*	*class war*
brass neck	*second referendum*	*Russian report*	*terrorist sympathiser*
tough time	*party leader*	*billionaire tycoon*	*anti semitism*
bad night	*trick pony*	*tory manifesto*	*free broadband*
lead balloon	*good speaker*	*fact check*	*blistering attack*
train wreck	*heartbreaking miscarriage*	*serial liar*	*anti semite*
tough crowd	*fantastic tonight*	*magic money*	*anti apartheid*
rough ride	*good tonight*	*compulsive liar*	*money tree*

Table 2. Multiword keywords

When paying attention to the women's corpus, a different scenario can be seen. What is commented in the tweets does not refer to their attitudes but to the feelings the audience has towards them. Sturgeon is criticised because the focus of her campaign was Scotland, i.e., *Scottish independence, confirmatory referendum* and *second referendum*. Yet, at the same time, her debate strategy was applauded (*good speaker, fantastic tonight* or *good tonight*) but also considered *boring*. Unlike the men's corpus, personal issues, such as a *miscarriage*, are mentioned on the tweets. As Kuperberg (2021) states in her study, this information, which is not necessary to be a politician, aims at making Sturgeon a failed woman for not being able to have a child. As for Swinson, all the keywords insult her and negatively describe her performance that night, i.e. *brass neck* [go down like a] *lead balloon, tough time, bad night* or *train wreck*. The only word referring to her policies is *bedroom tax*. Thus, the lexical choice used to address her intend to hurt focusing on her performance instead of her policies, as seen in (4)-(7).

(4) Nicola Sturgeon is simply **boring**.

(5) Please save us the ear ache of Nicola Sturgeon. Cancel cancel cancel!! SNP leader Nicola Sturgeon's **heartbreaking miscarriage** and why she spoke out about it.

(6) Did Swinson really just say to the fella wanting a 2nd referendum that Libs were the answer? She has some **brass neck.**

(7) It's just all falling apart and her policy ideas are going down like a **lead balloon.**

Since the aim of this paper is to compare and contrast the language used on Twitter to refer to Johnson, Corbyn, Sturgeon, and Swinson, the following step in our analysis is to examine their collocates. In other words, to judge a candidate by the company they keep (in this case, words). Word sketch processes the word's collocates and other words in its surroundings. The results are organised into categories, called grammatical relations, and for the purpose of this study, we will centre our attention on adjective predicates collocating with each candidate's last name, as "they modify nouns directly, in the so-called attributive construction" (Baker, 2004: 193).

Table 3 shows the fifteen most frequent adjective predicates that collocate with the four candidates' last names together with the normalised frequency[4].

Swinson	*Sturgeon*	*Johnson*	*Corbyn*
bad (146.1)	*impressive* (122.4)	*awful* (27.4)	*neutral* (29)
awful (122.4)	*excellent* (73.1)	*poor* (20.3)	*antisemitic* (28)
terrible (89.5)	*boring* (38.4)	*dreadful* (5.1)	*excellent* (24.2)
poor (63.9)	*fantastic* (31)	*atrocious* (4.6)	*brilliant* (23.4)
dreadful (45.7)	*brilliant* (31)	*untrustworthy* (4.6)	*impressive* (15.8)
useless (31)	*strong* (27.4)	*hopeless* (4.6)	*anti-Semitic* (15.2)
dire (23.7)	*confident* (18.3)	*horrendous* (4.6)	*clear* (15.2)
catastrophic (21.9)	*competent* (16.4)	*full* (4.1)	*anti-semitic* (14.2)
desperate (20.1)	*outstanding* (16.4)	*bloody* (4.1)	*unelectable* (14.2)
right (20.1)	*decent* (9.1)	*unable* (4.1)	*first* (14.2)
honest (20.1)	*sharp* (9.1)	*shocking* (4.1)	*OK* (11.7)
horrendous (14.6)	*credible* (9.1)	*disastrous* (4.1)	*popular* (8.1)
painful (14.6)	*cool* (9.1)	*abysmal* (3.6)	*anti* (8.1)
weak (14.6)	*superb* (9,1)	*painful* (3.6)	*honest* (7.6)
delusional (12.8)	*solid* (9.1)	*embarrassing* (3)	*happy* (7.6)

Table 3. Adjective predicates of "Swinson", "Sturgeon", "Johnson", and "Corbyn"[5]

There are some adjective predicates that collocate with more than one candidate. For example, in the female corpus, *interested, clear* and *good* collocate with both "Swinson" and "Sturgeon". These three words are more frequent with the latter than with the former, particularly *good*, which retrieved 137 hits (250.2) in the case of Sturgeon but only 43 (78.5) with Swinson. Likewise, in the male candidates' corpus, *good* is an adjective that occurs with both last names; however, it is far more frequent in Corbyn's (91.5) than in Johnson's subcorpus (13.2).

As shown in table 3, most adjective predicates collocating with Swinson (13 out of 15) have negative connotations. However, in Sturgeon's subcorpus,

[4] Numbers between brackets refer to the normalised frequency which has been calculated due to the different corpus size. In this case, the frequency is per 1,000,000 words.

[5] Gerunds used to make the continuous form of verbs have been excluded from the results, such as *struggling* or *appalling*.

most of them (14 out of 15) refers to positive adjectives. Similarly, most adjective predicates referring to Johnson are negative (13 out of 15), whereas most of them are positive in Corbyn's subcorpus (10 out of 15). Certainly, there are many negative adjectives that appear in both Swinson's and Johnson's subcorpora, i.e., *awful, poor, dreadful, horrendous* or *painful*. However, they are far more frequent in Swinson's than in Johnson's, although the former subcorpus is smaller in size than the latter. It is also worth mentioning the absence of some of these adjectives in the male candidates' corpus. Adjectives such as *useless, weak* or *competent* (0.83, 1.01 and 0.68, respectively in the females' corpus) retrieved 0 hits in the males' one. Interestingly, *competent* is normally used to compare both female candidates, as can be seen in (12).

(8) For what it's worth I think Swinson is **useless** but that's not the point.

(9) Sturgeon is the most statesmanlike but **useless** to rest of UK and thinking about PM.

(10) Swinson the **weakest** of all four.

(11) Sturgeon was honest, but she appeared **weak.**

(12) Swinson was dreadful and Sturgeon was **competent**.

If we compare the collocations from all the candidates, table 3 shows that most adjectives have a negative evaluation. Johnson is not very popular. Corbyn is strongly criticised for alleged anti-Semitism and his empty promises. Sturgeon, on the one hand, is attacked because she is focused on Scotland; and on the other, she is perceived as a solid, calm but boring candidate. Finally, Swinson is strongly attacked by Twitter's users in our corpus, using sarcasm to describe her political views. Sturgeon was the only candidate who had positive collocations regarding her performance during the debate. The differences we found between Sturgeon and Swinson are considerable. While Sturgeon is seen as an *excellent, solid* and *calm* candidate, Swinson is described as *weak* and *dreadful*. We will keep examining those differences in the next section of our analysis.

Last but not least, to close this section, we would like to comment on the presence of some misogynist words whose frequency is not statistically significant but the fact that they appear in the corpus is relevant for our study.

Taking into account the compilation of sexist words made by Sacraparental (2016), many of them have been found in our corpus, as seen in table 4.

Words punishing women's behaviour but acceptable for men	*bossy*, *abrasive*, *a ball-buster*, *aggressive*, *shrill*, *bolshy*
Words insulting women's sexuality	*slut*
Words about physical appearance not used for men	*mumsy*
Words praising women's behaviour	*flirty*
Words related to hormones	*hysterical*, *emotional*
Words defining women by their relationship to men and children	*housewife*

Table 4. Sexist words present in the corpus referring to "Swinson" and "Sturgeon"

Interestingly, the word emotional has a completely different use in the males' corpus than in the females' one, as can be seen in (13) – (14).

(13) Swinson really did bomb. Young, inexperienced and emotional towards the end and she knew she had blown it.

(14) Corbyn only offers class envy and emotional blackmail.

Whereas in (13) the user is referring to Swinson's feelings, example (14) makes reference to the type of blackmail which has nothing to do with Corbyn's feelings.

4.2 *Lexicon-based sentiment analysis*

As previously mentioned, when applying sentiment analysis techniques to a text, words are assessed according to their polarity. For this reason, in this paper, we will examine two different aspects of the tweets addressed to each politician. Firstly, the analysis will be carried out at word level, that is, positive and negative words will be extracted to see the difference between the ones related to female candidates and the ones related to male. Secondly, the corpora will be studied at text level. In other words, we will explore the overall sentiment of the viewers towards each candidate paying attention to the differences drawn between the female and male corpora.

Regarding the first analysis using the BING lexicon, we focused on the negative words which were more frequent in each corpus as we wanted to determine whether there was abusive language or not when talking about female candidates. Figure 1 and figure 2 show the most negative words addressed to women and men, respectively.

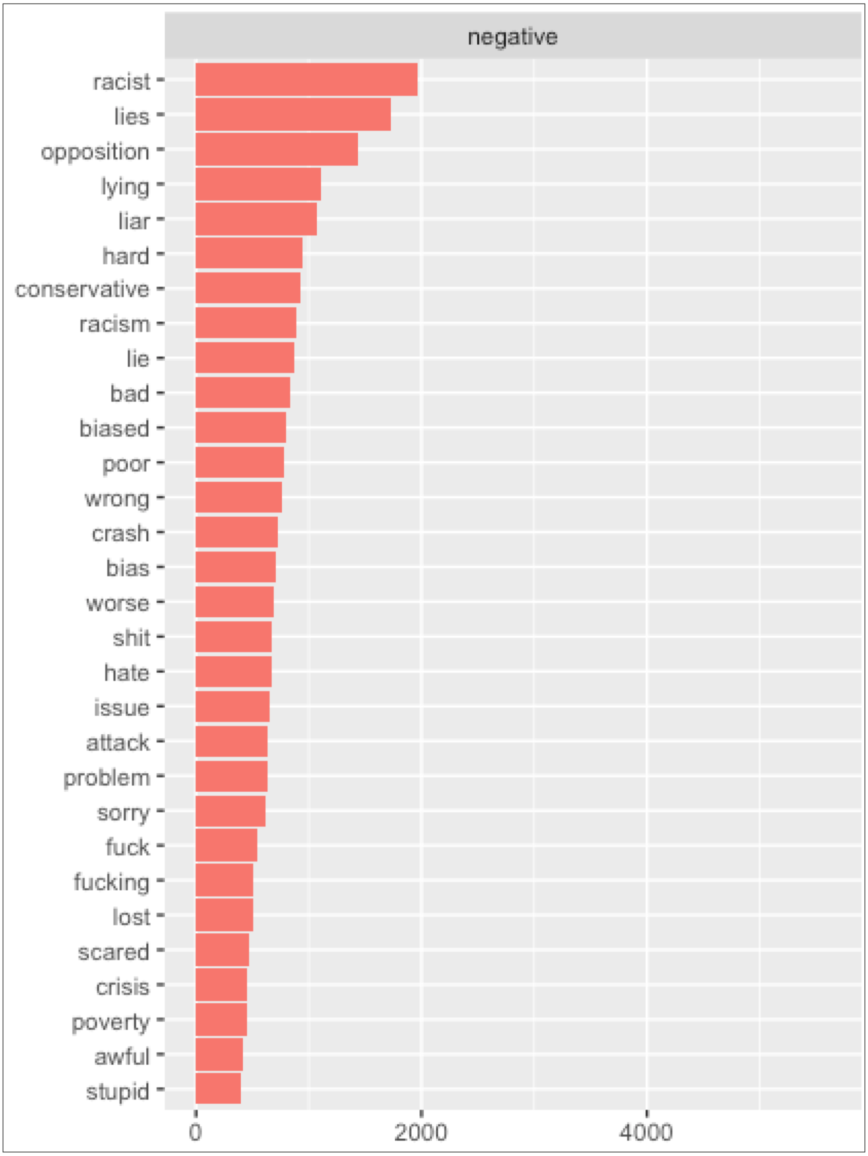

Figure 1. Top negative words in the male in candidates' corpus

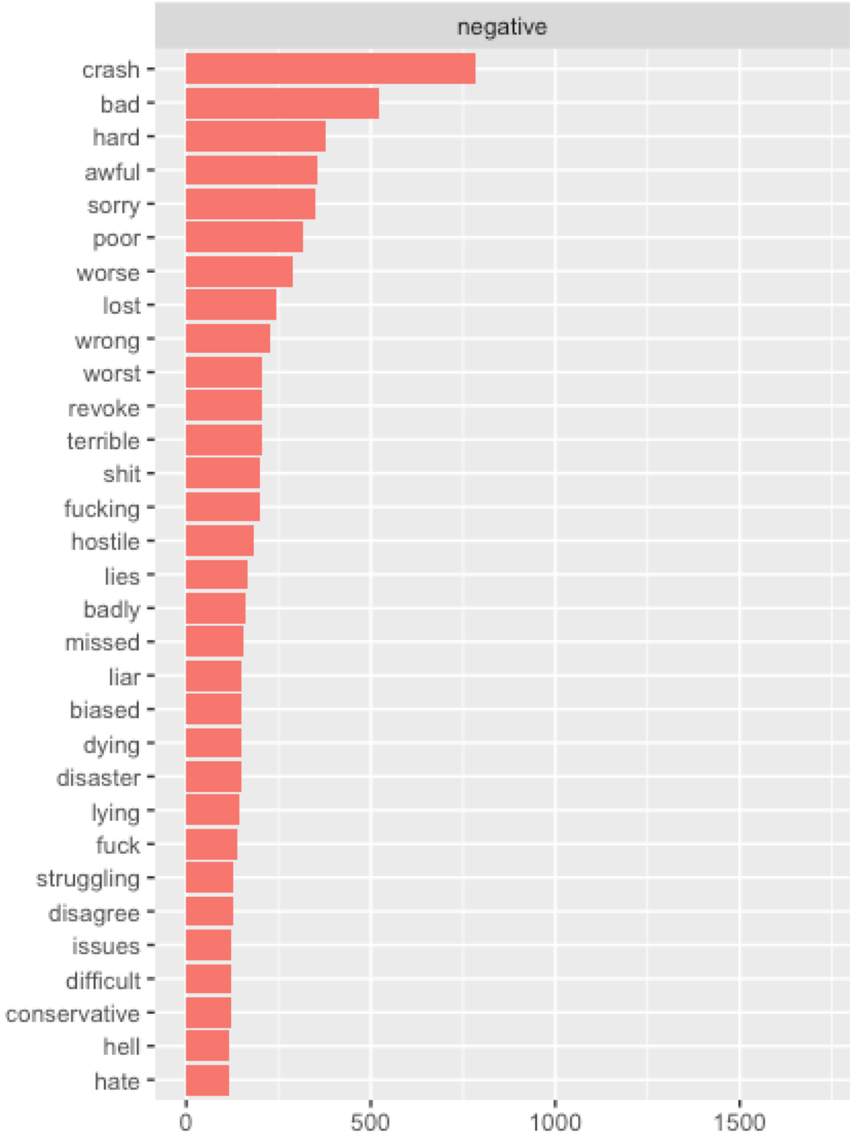

Figure 2. Top negative words the female candidates' corpus

As can be seen, there are some words which are common to both corpora, mainly words related to politics and its practice, such as *conservative*, *biased* or *issues*[6]. However, there are some differences which are noteworthy. Regarding the male candidates' corpus, there are words related to topics such as *racism* and *war*, which barely appear in the female candidates' corpus. As for *racism*, we found instances like *racist* or *racism*, which are two of the most negative frequent words, mainly used to refer to Corbyn. In relation to *war*, we first thought its use was related to war metaphors since they usually appear in public discourse, such as newspapers, political discourse or even marketing (Flusberg et al., 2018). However, most of the occurrences refer to the literal meaning of the word. Words such as *attack* or *terrorist* are also present in this corpus. Again, most of them appear in Corbyn's corpus, possibly because the last time there was a Prime Minister from the Labour Party, Tony Blair (1997-2007), the UK went to war (Iraq and Afghanistan), so the audience was afraid that Corbyn would involve the UK in another war. Additionally, the viewers declared that Corbyn had started a "class war" with the Labour's manifesto.

In the corpus of tweets mentioning female candidates, we found words such as *terrible, difficult, hell,* or *hostile*. In (15)-(18) some examples can be seen. The first example, *terrible*, made reference to the candidates' performance in the debate:

(15) Swinson has given a **terrible** performance!

(16) I thought Nicola Sturgeon was **terrible**.

(17) Jo Swinson is **terrible** in every possible way.

(18) Two **terrible** characters. [Swinson and Sturgeon]

Regarding the words *difficult* and *hell*, the former referred to the questions made in the debate, whereas the latter was used to emphasise or to be offensive, as shown in (19)-(22).

(19) That's way too **difficult** for Sturgeon.

(20) It was **difficult** for her [Sturgeon] with a U.K. audience.

(21) Why the **hell** is Nicola Sturgeon on a leaders debate for UK election? She is not a Westminster MP. She cannot be Prime Minister.

[6] According to Cambridge Dictionary, *issues* is a synonym of *problem*, whereas *conservative* refers to "not usually liking or trusting change, especially sudden change". However, in the corpus, *conservative* refers to the political party.

(22) Nicola sturgeon is one **hell** of a woman[7].

However, the word *hostile* was only used to refer to the audience's attitude towards Swinson, as the following tweets illustrate:

(23) Jo Swinson is tanking and the audience is deeply and increasingly **hostile** towards her.

(24) Am certainly not an uncritical admirer of Jo Swinson but felt the audience was from the start more **hostile** to her than a randomly selected audience.

Actually, tweets mentioning women candidates contain more negative words (46,275.8) than those referring to men candidates (43,347.8). But in the women's corpus, there are more than just negative words. As can be seen in examples (25)-(28), viewers still insult women just because they are women, making reference to physical attributes when talking about them, and stereotypes such as women being weaker and more sensitive than men.

(25) Has hell frozen over? Are pigs flying? Is Jo Swinson no longer a cunt? What's going on.

(26) Jo Swinson has amazing breasts but terrible teeth.

(27) Well Jo Swinson is absolutely terrible looks like she's gunna start crying any minute.

(28) Jo Swinson and her Kwasia party need to get the hell off the stage man.

(29) Jo Swinson and Nicola Sturgeon two peas in a pod & zero #leadership credibility, both out of touch with the electorates because they want to prove a point #LostThePlot #illiberalUndemocracts.

(30) Missing out Swinnocchio, as my wife said "I can't even listen to THAT woman", and I had to agree.

(31) Be careful, Swinson's got her knockers out.

(32) Jo Swinson voice is really irritating.

[7] *Hell of a*... can be either positive or negative, it depends on the context, which we do not have.

This does not mean that male candidates were not insulted on Twitter during the debate, but they were not judged according to their gender. For example, one of the most frequent insults that was used against male candidates was *liar* (412), whereas it was not as frequent when referring to female candidates (218). Additionally, when referring to Corbyn, they also called him *terrorist* and *racist*. Nevertheless, none of these insults made reference to the men's physical appearance or their fitness for occupying office, as happened with Swinson or Sturgeon.

According to the NRC lexicon, and as can be seen in figure 3, the prevailing sentiment for all the candidates is positive, with the exception of the tweets referring to Swinson, which are slightly more negative than positive. Tweets addressing female candidates are more related to feelings of sadness (2,266.8 vs. 2,048.4) and fear (2,144.1 vs. 1,930), with words such as *leave, tough*, *awful* or *revoke*, and words like *hostile*, *terrible*, or *dying* respectively. Contrariwise, male candidates' tweets have more words related to the feeling of trust (3,160 vs. 2,954.1), using words such as *leader*, *trust*, *truth*, *policy* or *neutral*. These results illustrate how our society still trust male candidates over female candidates. In fact, when talking about the possibility of a woman being the next PM, the feeling expressed is fear.

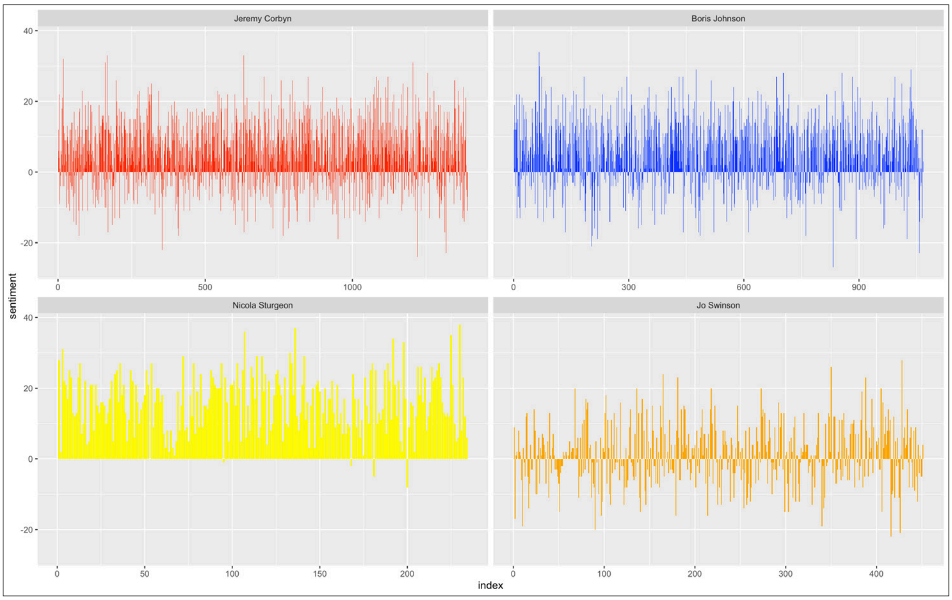

Figure 3. Comparison of the overall emotion

5. Conclusions

Political debates have been shown to be a way of equalising leaders from different political parties giving the same exposure to all of them regardless of their importance or presence in society. However, this paper has shown that this equality has not reached gender yet. As can be seen, tweets mentioning Sturgeon and Swinson present what has been called semiotic violence as they include abusive language when compared to the tweets mentioning Johnson and Corbyn. The audience is still misogynist when thinking about the possibility of having a woman as a leader or Prime Minister, as can be seen from the results obtained in this study. When giving their opinion, users tend to use language choices to hurt women referring to their unfitness for reaching such high positions in politics.

Generally speaking, tweets referring to women use more negative words than those referring to men. Viewers seem to trust more a male candidate, whereas they feel *fear* when facing a female one. It appears that the idea of having a woman as ruler is still really far for many people.

Women get to be respected when they reach a good balance of femininity and traditional men-like manners in politics, such as Thatcher did when she was PM. It is interesting that, when comparing both women candidates' corpora, we found more sexist comments towards Swinson than Sturgeon. Maybe this was due to how they present themselves as politicians: while Sturgeon, First Minister of Scotland, presents herself as a strong and calm candidate; Swinson, the youngest member of the House of Commons (2005-2009), is a more feminine, young, and ambitious woman.

In spite of this, the UK general election of 2019 brought more women in Parliament with a total of 220 female MPs elected of 650 seats[8]. This is 12 more than the previous high of 208 in 2017. For the first time, both the Liberal Democrats and Labour have more women MPs than men. Of Labour's 202 MPs (excluding Speaker Lindsay Hoyle), 104 are women; and of the Liberal Democrats' 11 MPs, 7 are women. Internationally, nowadays there are 10 women serving as Head of State and 13 serving as Head of Government. These numbers are hopeful, but if we want women to stay in the political scenario, we need to start treating them fairly.

8 House of Commons Library: https://commonslibrary.parliament.uk/research-briefings/sn01250/ [Accessed 01/05/2021]

These results should not be overlooked, and solutions need to be implemented. Anonymity should not be an excuse to insult women and to express misogynist behaviours. As has been shown, if we want women in the political arena, we need more applications, research, and initiatives to raise awareness and curb such unjustified attacks that women have to suffer just because of their gender. There are already attempts to tackle this problem, such as ParityBOT (Cuthbertson et al., 2019) or Plaza-del-Arco et al.'s (2020) initiative to detect misogyny in Spanish tweets. Needless to say, society needs to continue working on this so that we could get real equality at last.

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