Title: Online Extremism and Islamophobic language and sentiment when discussing the Covid-19 pandemic and misinformation on Twitter

Abstract
This paper looks at the profiles of those who engaged in Islamophobic language/extremist behaviour on Twitter during the COVID-19 pandemic. This two part analysis takes into account factors such as anonymity, membership length and postage frequency on language use, and the differences in sentiment expressed between pro-social and anti-social tweets. Analysis includes comparisons between low, moderate and high levels of anonymity, postage frequency, and membership length, allowing for differences in keyword use to be explored. Our findings suggest that increased anonymity is not associated with an increase in Islamophobic language and misinformation. The sentiment analysis indicated that emotions such as anger, disgust, fear, sadness and trust were significantly more associated with pro-social Twitter users whereas sentiments such as anticipation, joy and surprise were significantly more associated with anti-social Twitter users. In some cases evidence for joy in the suffering of others as a result of the pandemic was expressed.

Keywords Islamophobia**;** Covid-19**;** Muslim**;** Islam**;** Hate Crime**;** Online

References – Appear at the end of this paper

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Max wordcount: 9000 words for standard articles / 12000 for review articles - all material included except tables and figures
Word Count: 8, 486

Tables and /or Figures (if relevant)
11 Tables in total

Acknowledgments (if relevant) N/A

Funding information (if relevant)

Funding received from the Economic and Social Research Council – grant number ES/V004840/1

Ethics statement (if relevant) - more details can be found here
Full ethical clearance was granted by the Birmingham City University ethics and research committee

Introduction

With over 4.66 billion active users (Lin, 2021) the internet is characterised by hyperconnectivity, which facilitates spontaneous and global communication for users with multiple others (Edwards et al., 2021). This has presented a global issue where the phenomena of digital wildfires (the rapid circulation of content) has seen the spread of harmful and misleading content being circulated online, becoming viral and in effect leading to the marginalisation and damage of the wellbeing of individuals and communities (Edwards et al., 2021). As such, the threat of online extremism poses both disruption and damage to the social fabric of many communities (Jerard, 2019). Ranging from cyberbullies to terrorist organisations (Klausen, Marks and Zaman, 2018), online extremists utilise a variety of online spaces to radicalise and incite violence. There are various factors that have been used to develop definitions for extremism, for example, the (non)democratic nature of the political system, the structure of values, ideologies, ethnocentrism, and political objectives to name a few (Sotlar, 2004). To date there is no universal definition for extremism and is largely based on location and the structure of a particular state. The UK Government Prevent Strategy defines extremism as the 'vocal or active opposition to fundamental British values, including democracy, the rule of law, individual liberty and mutual respect and tolerance of different faiths and beliefs' (HM Government, 2011). Yet, the difficulty in providing a widely accepted and agreed upon definition for extremism has been compared to issues faced when defining pornography, "essentially, you cannot define it, but when you see it, you recognise it easily" (Sotlar, 2004: 1).

Social media networks support interpersonal communication and collaboration using internet-based platforms, such as Facebook and Twitter (Kane et al., 2014), which have become a highly effective platform on which extremist content can be inexpensively shared and circulated (Nouh, Nurse, and Goldsmith, 2019), often leading to the disruption of racial and religious harmony (Jerard, 2019). Findings have shown that the polarisation of extremist content online is fostered through the echo chamber environments which amplify extremist ideologies on such networks (Barberá, 2020). Research has demonstrated differences in the types of interactions on social media sites and how this can impact levels of extremist content. For instance, Facebook encourages strong relationships across users, whereas sites such as Twitter are regarded as a stronger facilitator of information dissemination (Gruzd et al., 2011), which provides a platform that allows for echo chamber environments (Gruzd and Roy, 2014). The emergence of extremism online and specific types of online harms can be contingent on trigger events. Like offline behaviour, the prevalence and severity of hate crimes (Chakraborti and Garland, 2009) are influenced by 'trigger' events of local, national and international significance (Williams and Burnap, 2015), similar phenomena can occur online. Trigger events can elicit individual or communal calls for action or revenge. Often, these events include violence against in-groups, police brutality, contested elections, and provoking acts by hostile outgroups or conflict inducing speeches by public figures or politicians (Staun, 2008).

Research has attempted to postulate possible predictive factors for online extremism. Findings demonstrate how accounts with high anonymity, low membership length and low postage frequency are significantly more associated with extremist language online (Sutch and Carter, 2019). The deindividuation theory help explain how anonymity causes group members to fail to perceive themselves and others as individuals (Zimbardo, 1969), this deindividuation weakens the inhibitions against non-normative behaviour (Festinger et al., 1952). Where individuals are anonymous and have a lack of perceived responsibility, individuals are more likely to ignore normative restrictions and behave as they wish (Cinnirella and Green, 2007). This has specifically been proven to be the case for online communication (Christopherson, 2007), as anonymity minimises the perceived differences of an individual online, which can cause individuals to identify with a group, which increases the chance of polarisation towards extreme positions (Lee, 2006). Contrary to the findings of Sutch and Carter (2019) previous research looking at the role of membership length has found that in fact an extended membership length is significantly correlated with an increase in extremist attitudes (Moscovici and Zavalloni, 1969) - although this research is quite outdated. Researchers have also suggested how research in this area has previously been superficial (Stroud, 2010). There have also been mixed findings when looking at the role of postage frequency. Although Sutch and Carter (2019) found that low postage frequency acted as a predictor of extremism online, prior research had found that higher engagement can result in a shift towards negativity and extremism (Del Vicario et al,. 2016). Due to the inconsistencies within these findings, it is important to address the true nature of the role of postage frequency (Wojcieszak, 2010).

The combination of the role of social media as a platform to freely exchange viewpoints and opinions, and the role of extremism and trigger events, has facilitated the emergence and circulation of misinformation, conspiracies, and fake news. Importantly, misinformation should not be confused with disinformation, with the former referring to the inadvertent sharing of false information, and the latter referring to the deliberate creation and sharing of false or manipulated information intended to mislead or deceive audiences (Digital, Culture, Media and Sport Committee, 2019). Given the role of the user in spreading misinformation, understanding the user motives is of particular importance, especially when informing the design of interventions. Research indicates that misinformation can be reshared by users due to failures in considering or thinking sufficiently on whether what is being shared is true or not (Pennycook et al., 2020). Confounding factors which may reduce the extent by which a user considers the content which they share might also include the ease at which information can be reshared (a simple click of a button) (Pourghomi et al., 2018), as well as the environment in which a user interacts with online content and misinformation i.e., if the user is distracted in some way, such as when travelling (Pantazi et al., 2018). Moreover, the presentation of misinformation might also make it more believable. Research indicates that language or messages which possess more emotional valence can often make something more believable (Martel et al., 2020). As misinformation can often comprise of emotive and less scientific language (Falade and Colutas, 2017), it is comparatively more believable by users than scientific information, which can often comprise of less emotive and more dismissive language (Lavorgna and Myles, 2021).

There are several other perspectives which explain why misinformation is readily believed and subsequently shared. For instance, the misinformation effect, a theory from the field of cognitive psychology, which proposes that misinformation can often be perceived as truth or factual if it appears as an equivalent to truthful information (Challies et al., 2011). Often a feature of memory and recollection research, in the context of Covid-19 and misinformation, users may believe fake news if such information appears similarly to real news, such that it is perceived as an equivalent (therefore regarded as equally authentic and reliable). Other concepts relate to the role of individual bias, with people being less sceptical if the information presented aligns with their political beliefs (Gampa et al., 2019). Of notable mention are the five criteria for which Schwarz et al. (2016) argues individuals subject a piece of information to before deeming it as true. For instance, compatibility with other known information, the credibility of the source, whether it is believed by others, whether it is internally consistent with their views or beliefs, and whether there is supporting evidence (Apuke and Omar, 2021). Previous research has found that subjecting information to these criteria in the context of social media might not necessarily be an effective method at preventing the belief and sharing of misinformation (Cinelli et al., 2021). Van Der Linden et al. (2020) support the theory of psychological inoculation, otherwise referred to as pre-bunking. The theory proposes that the challenge to be inoculated against (in this context, fake news and misinformation) must be weakened to such an extent that it will trigger stronger tendencies in the individual to critically think (Compton, 2013). The intervention is most effective when participants are first warned that their attitudes are under threat or attack, followed by the pre-emptive exposure to counterarguments. Studies focusing on climate misinformation note that following psychological inoculation, participants were less receptive and more resistant to climate misinformation (Maertens et al., 2020).

The virality of online hate in the context of Covid-19

The Covid-19 pandemic generated a persistent influx of harmful content on social media, it triggered the proliferation of various forms of extremism, misinformation, conspiracy theories and fake news. In response to an insurgence of misinformation and fake news that rapidly circulated online, the World Health Organisation (WHO) warned of an on-going ‘infodemic’, where misinformation was widely propagated across both mainstream and social media platforms (World Health Organization, 2020b; Zarocostas, 2020). For example, research shows that over 25% of the most viewed Covid-19 YouTube content (which reached over 62 million users) contained misleading information (Li et al., 2020). Moreover, 46% of the United Kingdoms and 48% of the United States population have reported being exposed to misinformation and fake news around Covid-19 (Ofcom, 2020; Mitchell and Oliphant, 2020). This includes conspiracies which concern the origin of the virus, ranging from it being bioengineered in a lab in Wuhan, China or bioengineered in the US to disrupt China’s economy (Ali, 2020; Andersen et al., 2020) to how hydroxychloroquine can fight the virus, as promoted by Donald Trump, the president of the United States, and Jair Bolsonaro, the president of Brazil (Spring, 2020). Of significant concern was how such misinformation undermined public health interventions and response strategies, led to self-induced hospitalisations, and criminal activity. For example, following the endorsement of hydroxychloroquine as an effective treatment to Covid-19, there was an increase in mass poisonings and overdoses (Spring, 2020). Similarly, the claims that 5G technology can exacerbate the symptoms or susceptibility to Covid-19 lead to inspired arson attacks on phone masts, as well as assaults on telecommunication workers (Spring, 2020). Moreover, widespread misinformation increased aversion to following guidance from health officials and experts, which in-turn instigated vaccine hesitancy and rejections (Freeman et al., 2020; Uscinski et al., 2020).

With the internet acting as an echo chamber, users capitalised on the Covid-19 pandemic to proliferate pre-existing discriminatory beliefs towards British Muslims and Islam in general as well through conspiracy theories that connected these communities to the virus in various ways (Awan and Zempi, 2015). Our paper explores how these irrational beliefs and thoughts were disseminated on social media, covering important coverage of communications surrounding conspiracy theories online whilst paying attention to the content associated to racist ‘infodemic’ messages.

Online hate was distinctly targeted towards the Muslim community, the online response to the Covid-19 pandemic has been characterised by a significant increase in Islamophobic related extremism, most of which related to accusations that Muslims are responsible for spreading the virus, or that Islamic rituals were violating Covid-19 restrictions (Bakry et al., 2020; Nagar and Gill, 2020). When confronting such elements of Islamophobia it is important to understand how social and cultural capital can impact localised communities. Fuelling significant hate and ostracisation of Muslims, India media outlets such as "The Hindu" encouraged hate towards Islam following the printing of caricatures depicting a Covid-19 shaped virus wearing Muslim clothing (Bakry et al., 2020). Given the function of social media as a place for discussion and interactions, hashtags such as #coronajihad quickly became viral, further perpetuating a more substantial role of Muslims in the Covid-19 pandemic (Dearden, 2020). Further instigations of Islamophobia were inspired by claims that Muslims were spreading Covid-19 by spitting on policemen as well as fruit, food, and utensils (Nagar and Gill, 2020). What is described as a 22-day frenzy of fake news, Indian government officials profiled a religious organisation known as Tablighi Jamaat and claimed that a religious meeting that had taken place was a major national Covid-19 source (Udupa, 2020). Some of those conspiracy theories have placed gatherings of an Islamic missionary organisation Tablighi Jamaat as the reason for the outbreak of Covid-19 and others have even claimed that Muslims have invented the virus to spread Jihad (Al-Astewani, 2021). Hindi news channels as well as some British channels used their platforms to spread misconceptions around Muslims and Covid-19, most of which became viral on social media platforms such as Facebook, TikTok, Helo and Twitter (Jadhav, 2020). In taking advantage of what was presented as state-sponsored profiling of a minority community, the far-right exploited the Covid-19 crisis to further their own agenda of calling for the persecution of the Muslim community.

Prasad (2020) found that the pandemic was used to promote Hindutva ideology (described as cultural nationalism) by asserting Muslims as the spreaders of the virus and constructing the community as a threat or enemy to the country. This ideological discourse was established through 3 stages; first, surface level validation, which refers to information that confirms a pre-conceived idea about a perceived enemy; second, inflammatory rhetoric which scapegoats the enemy and incites moral social panic; and third, an environment of fear and paranoia which curates symbolic and physical violence towards the perceived enemy (Prasad, 2020).

As was the case with Covid-19 conspiracies, the virality of online extremism and Islamophobia resulted in several transgressions to the offline world, including marginalisation, discrimination, and violence (Perrigo, 2020). Islamophobia in the UK has had a detrimental effect on Muslim healthcare workers, who have reported disproportionate difficulty in acquiring personal protective equipment, thereby being exposed to more risk (Akçakaya, 2021; Bi, 2020). Minority groups including Muslims have also experienced poorer mental health due to discrimination and marginalisation associated with Covid-19 (Jaspal and Lopes, 2021), as well as barriers to seeking health and testing due to the stigmatisation they have received (Mukherjee, 2020). Notable examples also include an incident where a Muslim woman was approached by a man in south London, who coughed in her face and claimed he had coronavirus (Hamill-Stewart, 2020), and where seven Muslim volunteers in India were assaulted by a group of local BJP members in April 2020 as they tried to distribute food to impoverished people in districts of Karnataka (Ellis-Petersen and Rahman, 2020).

Rationale

The aim of the research was to examine both language and sentiment used when discussing Covid-19 misinformation, Islamophobia and extremism. The focus of the current study is to analyse the treatment and attitudes towards Muslims online in the context of Covid-19. During the pandemic, Twitter had been a source of interaction, reaction, and (mis)information and was therefore a potentially rich source of data. Misinformation during a global health event can cause harm to individuals and communities. When paired with already rife online Islamophobia there is a clear need to investigate further to identify contributing factors, reactions, and how this might shape responses in the future to reduce such online misinformation and hate. Whilst Twitter can involve a global audience and user base the focus is on English speaking user data. At present, the UK government has no legislation designed to regulate the accuracy and legitimacy of news or information shared online, however new laws may materialise in response to the Online Harms Whitepaper (2019) which could improve overall investment and attention to reducing the spread of false information.

Methods

Our approach involved two separate stages of analysis. One with a quantitative focus on language and the comparison of language used between different user types. This would involve categorising users and their tweets based on their levels of anonymity, membership length, and postage frequency (in line with the method used by Sutch and Carter, 2019) and then using corpus linguistic analysis to explore differences in language use between users. The second approach involved using a smaller subset of the originally collected tweets, but instead using sentiment analysis to determine if there were any differences in emotion or sentiment being expressed in these tweets quantitatively. In this case tweets were categorised as being pro-social or anti-social in intent (see below). Combining these forms of analysis allow for exploration of both the literal use of language as well as the emotion being actively expressed.

Data Collection and Sample

When employing corpus linguistic techniques there is not an agreed upon corpus size (Hiltunen et al., 2017), although Haber (2015) suggests that when employing these methods on Twitter 200 tweets per users is generally recommended as a minimum. To identify the users that tweets would be collected from, a word list containing 19 extreme words/phrases such as #banislam and #islamistheproblem was generated (see Appendix A). This word list was based on previous work (Awan et al., 2019; Sutch and Carter, 2019) and past use had generated a large volume and range of user accounts to then collect general tweets from. Once user accounts were identified a selection of the most recent tweets could be collected. To collect the original tweet data, software known as Twitter archiving google sheet (TAGS) was used as it performs automated collection for search results from Twitter based on search terms, hashtags and even use profiles. Through this process a total of 100 Twitter accounts and 100,545 tweets were examined (this number was reduced further for the sentiment analysis – see below). The tweets were collected over a period of 12 months, from January 2021 to January 2022. There was no geographic limit to where the tweets originated from, and often such location information is not included as part of the Twitter meta-data. However, the focus on English language tweets meant many tweets were from English speaking countries or users with English as a language. This is reflected in the content of the tweets which were often UK and US-centric, and the inclusion of tweets in reaction to events with large populations of English speakers (such as India). This limits any generalisation of the result to COVID-19 related Islamophobia to English speaking populations, rather than allowing more completely global comparisons.

Corpus Linguistic Approach

Corpus Linguistics is a text/word level approach that considers the relative frequencies of word occurrences, and patterns of word usage (McEnrey and Hardie, 2011). These data sets, or corpora, are collections of text that can number in the millions of words. It is possible to compare corpora and determine whether certain words, phrases or word pairs occurring statistically more frequently in one corpus than another. It is possible to determine whether certain words are more key or important within a text (used more than would be expected by chance alone) and which words share a certain linguistic space, again beyond that expected by chance. In the past it has, for example, been used to compare author or publication styles, to investigate language around sexuality (Baker, 2018), and political discourse (Orpin, 2005). Baker et al. (2013) demonstrated the effectiveness of utilising such methods to measure attitudes towards Islam, their study investigated language use in British newspapers relating to the word 'Muslim'. This form of analysis, although quantitative in nature initially, allows for the keywords analysed to be examined in social and cultural context. The original context and surrounding language are preserved when looking at the examples of word usage. We can see which words occur more frequently, but we can also examine all cases of that word use to see the full tweet or phrase.

In the current research, user accounts were scored based on the amount of personal identifiable information available (giving an anonymity score – higher values indicating the user was more identifiable/less anonymous). Each identifiable item (a name, a location, a personal profile picture/avatar etc.) added to the score to a maximum of seven. There are issues with operationalising anonymity as it is difficult to determine the legitimacy of accounts, this has been considered and the present research attempts to adopt a more exhaustive measure of operationalisation compared to previous attempts by other research, which only focused on user's names and whether they have a URL (Peddinti et al. 2017). These scores were then visually binned to produce discrete categories (low, moderate and high anonymity). A similar approach was taken to postage frequency with each user having an average number of tweets per month as a value (taken as a simple mean: total tweets divided by total months of membership). This again was visually binned to produce three categories (low, moderate and high postage frequency). For membership length the data of joining was used as the start point, and a value in months representing the total time spent as a Twitter member up to the point of data collection. This too was divided into three categories (low, moderate and high length). See Table 1:

[INSERT TABLE 1 HERE]

For the research presented here the corpus linguistic analysis was performed using AntConc computer software (version 3.5.7) (Anthony, 2018). The software can produce keyword lists and perform keyness comparisons between categories or corpora.

Sentiment Analysis Approach

This approach traditionally has been used within marketing to determine the perception towards products, services or adverts. In its most basic form, it is the simple recording of whether a response to an item is positive or negative (the polarity) and can be done either via manual classification of responses or by using data mining and machine learning (Pang and Lee, 2008). This approach has gradually become more sophisticated with the inclusion of emotional lexicons, and specialist lexicons. These are specific dictionaries where specific terminology is given a value, for example words associated with a positive response can be given a positive value, and those with a negative response a correspondingly negative value (Crossley et al. 2016). Comments and responses can then be parsed, and a value assigned to each based on the overall sentiment expressed.

Rather than simple positive or negative comparison much more subtle distinctions and measurements can be made. For example, EmoLex (Mohammed and Turney, 2013) is an emotional lexicon used within sentiment analysis that has two broad initial categories, positive and negative, and eight emotional categories: anger, anticipation, disgust, fear, joy, sadness, surprise, trust. This gives a much more fine-grained understanding of the emotional content of a response. For the research we present here this process was automated by the Sentiment Engine for the Analysis of Cognitive Emotion, or SÉANCE software (Crossley et al., 2016), and used the EmoLex emotional lexicon to calculate sentiment values.
As EmoLex was to be used by SEANCE to allow for a more fine-grained measurement of the emotions expressed, across several emotional categories this potentially increased the number of statistical tests (in this case t-tests) to be run. We therefore focused on comparisons between pro and anti-social tweets, across these emotional categories. By reducing the broader comparisons to two categories (pro and anti-social tweets) this reduced the number of tests being run, and ultimately reduced the potential for Type I errors in the final analysis.
The present research followed the operationalisation definitions used by previous research when looking at classifying pro-social and anti-social behaviour online (Sutch and Carter, 2019). Anti-social behaviour can be classified by acting in a manner which has or is likely to cause harassment or distress to others who are not part of the same household (Berman, 2009; The Crime and Disorder Act, 1998). Pro-social behaviour is an action which has a sole intention to benefit or provide help to other individuals (Padilla-Walker and Carlo, 2015), it is particularly evident in the form of protection from aggression (Amichai-Hamburger et al., 2015). If they could not be assigned or were unclear, they were not included resulting in a reduced overall sample size of 40,34 tweets. The sentiment analysis therefore used approximately 40% of the tweets from the original sample of 100, 545 used in the corpus linguistic analysis.

Hypotheses

This research hypothesised that Twitter accounts with high anonymity (characterised by a low number of identifiable items), low membership length and low postage frequency will be significantly more associated with extreme words. The research hypothesised that scores for EmoLex categories such as Anger, Disgust and Fear would be significantly more associated with antisocial tweets, whereas scores for EmoLex categories such as joy, surprise and trust would be significantly more associated with prosocial tweets.

Results

Corpus Linguistic Analysis

A series of corpus linguistic analyses were conducted on 100,545 tweets from 100 Twitter users. A wordlist containing 28 words, which represented Covid-19 and Islamophobic related hashtags/search terms was generated. This wordlist was based on the previous Twitter and corpus-based research (Awan et al., 2019; Sutch and Carter, 2019), as well as broader research on language commonly associated with Islamophobia (Awan, 2014; Baker, 2018). This includes terms and phrases such as ‘Muzrat’ and ‘Islamiscancer’ for example. Using AntConc software (Anthony, 2004; Anthony, 2018) a total of nine Keyness analyses were performed on the three categorical variables of anonymity, membership length and postage frequency. Keyness analysis allows researchers to evaluate whether a word occurs more frequently in a target corpus as compared to its occurrence in the reference corpus, indicating that the word maybe a key term of the target corpus (Scott, 1997). When looking at Keyness results it is important to note that negative Keyness values represent words which are unusually infrequent compared to words in a reference corpus (Anthony, 2004).

[INSERT TABLE 2]

[INSERT TABLE 3]

[INSERT TABLE 4]

The tables above represent the comparisons for the three levels of anonymity. Results illustrate that the low anonymity corpus contains more words which occur significantly more frequently when compared to both the high anonymity corpus and the moderate anonymity corpus. These findings suggest that low levels of anonymity may be predictive of increased Islamophobic language use. Specifically, low anonymous users, those who are more identifiable online are much more likely to use extremist terms than those with high anonymity or moderate anonymity.

[INSERT TABLE 5]

[INSERT TABLE 6]

[INSERT TABLE 7]

The three tables above represent the comparisons for the three levels of membership length. Results illustrate that the moderate membership length corpus contains more words which occur significantly more frequently when compared to both the low membership length corpus and the high membership length corpus. These findings suggest that Twitter users with a moderate membership length are much more likely to use extremist terms than those with low to high membership length.

[INSERT TABLE 8]

[INSERT TABLE 9]

[INSERT TABLE 10]

The three tables above represent the comparisons for the three levels of postage frequency. Results illustrate that the low postage frequency corpus contains more words which occur significantly more frequently when compared to both the moderate postage frequency corpus and the high postage frequency corpus. These findings suggest that Twitter users with a low postage frequency are much more likely to use extremist terms than those with moderate to high postage frequency. Overall, the corpus linguistic analysis has demonstrated that extreme language used online relating Islamophobia and misinformation during the covid-19 pandemic was significantly more associated with accounts that demonstrate low levels of anonymity moderate levels of membership length and low levels of postage frequency.

Twitter Sentiment Analysis

As can be seen in table 11 there appear to be only marginal differences in the mean scores for each EmoLex category between Prosocial and Antisocial Tweets. Some larger differences can be seen in some areas with higher mean Anger, Sadness and Fear for Prosocial compared to Anti. With notably higher mean Joy for the Antisocial.

[INSERT TABLE 11]

Given the independent design (IV Tweet Type: Pro or Antisocial) a series of independent t-tests were run for the eight EmoLex categories. The t-tests revealed a significant difference ($ps < .05$) in all comparisons. Reflecting significantly higher mean scores for Anger, Disgust, Fear, Sadness, and Trust in Prosocial Tweets compared to Antisocial tweets. This also reflects significantly higher means scores for Anticipation, Joy, and Surprise in Anti-social Tweets compared to Prosocial.

Discussion

Corpus Linguistic Analysis

The present research did not support the hypothesis outlining that Twitter accounts with higher anonymity characterised by a low number of identifiable items would be significantly more associated with extreme words. On the contrary, it was discovered that Twitter accounts with low anonymity characterised by a high number of identifiable items were significantly more associated with extreme words. These findings appear to contradict previous research in the area which found that a high level of anonymity is significantly more associated with extremist content online (Awan et al., 2019; Sutch and Carter, 2019). The present research appears to dispute theories around deindividuation and online disinhibition effects. These theories elucidate how deindividuation weakens inhibitions against non-normative behaviour and how there is a difference between communicating online, whereby individuals can experience a sense of security in communicating online due to the ability to remain anonymous (Festinger, Pepitone, and Newcomb, 1952; Suler, 2004; Zimbardo, 1969). The current research did not support the hypothesis which outlined that Twitter accounts with a low membership length, characterised by zero to 1000 days active would be significantly more associated with extreme words. Rather, it was established that accounts with a moderate level of membership length, characterised by 1001 to 3000 days active were more significantly associated with extreme language. These findings dispute previous research which found that Twitter users with a low membership length were significantly more associated with extreme language (Sutch and Carter, 2019). The current research does somewhat support previous research which stated that having a higher level of membership length is associated with non-normative behaviour (Moscovici and Zavalloni, 1969). Although the current research found this relationship to be associated with moderate membership, this category is indicative of having an increased level of membership but is not at the high end of the scale.

As hypothesised, the present research found that Twitter accounts with low postage frequency, characterised by an average number of between zero and ten tweets per day, were more significantly associated with extremist language. These findings concur with previous research which also found that low postage frequency is a predictive factor of online extremism (Sutch and Carter, 2019). The research disputes wider findings that state that a higher degree of engagement is indicative of a higher level of extremist behaviour (Del Vicario et al., 2016). Although the findings regarding anonymity did not meet the hypothesis, the results have illustrated important theoretical ideas which require further attention. To explore plausible theoretical explanations for this it is crucial to take a closer look at the factors associated with the trigger event, Covid-19. When discussing the role of trigger events in the propagation of cyber hate it is important to highlight the work of Williams and Burnap (2016), which provided novel findings that demonstrated the ability to detect cyber hate in the aftermath of antecedent trigger events. For the current research the antecedent trigger event was Covid-19, when looking closely at this trigger event it was quite unique in the sense that it has been able to sustain continuous influxes on cyberhate since the beginning of the pandemic in 2020. This is significant, when looking at the work of Williams and Burnap (2016) their research around the Woolwich attack demonstrated that cyber hate had a half-life, whereby event specific cyber hate can be relatively short term.

The pattern and continued spread of cyberhate related to the trigger event of Covid-19 is quite unique and therefore it is not surprising that factors such as anonymity played a differential and lesser role in the propagation of cyber hate. In general, the protracted nature of Covid-19 pandemic may have had an impact on people remaining anonymous, as well as the shelf life of their Twitter membership. An explanation for these findings could be found by exploring the specific characteristics of the trigger event, how did misinformation, disinformation, xenophobia, fake news and conspiracy theories rapidly saturate the mainstream discourse around Covid-19 throughout the world. On many occasions throughout the pandemic this discourse has been peddled by senior politicians, governments, medical professionals and mainstream media. Schwarz et al. (2016) highlights how the credibility of the source plays a role in the dissemination and acceptance of information. In addition to this, research looking at authority and misinformation found that that the misinformation effect only occurred in the high authority conditions (Skagerberg and Wright, 2008). Both high credible and high authority individuals played a significant role in adopting and encouraging the dissemination of the above-mentioned discourse. Looking closely at India for example, it is evident through the actions of media outlets, such as ‘The Hindu’ which printed caricatures depicting a Covid-19 shaped virus wearing Muslim clothing, as well as the actions of the Indian government who profiled the Tablighi Jamaat as super spreaders causing a 22-fake news frenzy (Bakry et al., 2020; Udupa, 2020), played a significant role in the perpetuation of Islamophobia throughout the pandemic.

The current research argues that the role of anonymity can have a lesser effect when misinformation, disinformation, xenophobia, fake news and conspiracy theories have saturated the mainstream discourse. This could cause individuals to struggle to differentiate between information they are exposed to and favour the consensus of the majority which has been supported by individuals of high authority and credibility. This in turn dampens the need for individuals to hide behind anonymity when expressing their views. The findings around anonymity also present the idea that individuals online may be attempting to push the boundaries to see how far and extreme they can go online without being anonymous. If users online are more confident to express their true thoughts and ideologies online without the protection of anonymity, this could encourage the transgression of similar behaviour offline, which mean surges in offline hate and abuse.

Sentiment Analysis

The results from the sentiment analysis indicated that emotional sentiments such as anger, disgust, fear, sadness and trust were significantly more associated with pro-social Twitter users whereas sentiments such as anticipation, joy and surprise were significantly more associated with anti-social Twitter users. Initially these results seem counterintuitive as the supposedly positively framed prosocial tweets, tweets around combating misinformation and Islamophobia, scored highly for very negative emotional states. However, this appears to reflect the emotional response that prosocial tweeters are having to the negative content they encounter – that of the antisocial tweeters, spreaders of misinformation, and Islamophobes. They are directing in their comments anger towards these individuals, disgust at their behaviour and statements, fear of the impact it may have on their safety and that of others. These findings support previous research which found that pro-social behaviour is evident in the form of protection from aggression (Amichai-Hamburger et al., 2013; Lapidot-Lefler and Barak, 2015). Contrastingly the significant inclusion of joy in the tweets of those considered to be antisocial potentially reflects the satisfaction taken in being contrary, either through the process of trolling or potential enjoyment in the impact their statements have. It has been noted that high scores on the Dark Triad/Tetrad (with sadism being one of the scored traits) can be associated with antisocial online behaviour (Craker and March, 2016), and cyberbullying (Goodboy and Martin, 2015). If this applies in this context also it would explain the Joy and Anticipation present.

Conclusion

Overall, it is apparent that the composition of Twitter users who engaged in extremist Islamophobic behaviour on the platform during the Covid-19 pandemic differed from what was anticipated. Importantly findings around membership length and anonymity disputes previous research within this area, a novel finding. Contradicting assumptions about the role of anonymity plays in online extremism, as well as the assumed role of long-term immersion (membership length) or presence in an echo chamber like environment has on online extremism. Although findings surrounding the sentiment analysis of tweets diverged from expected findings, further consideration and application to wider literature indicates plausible reasoning for the presence of displayed sentiments. For example, it is likely that pro-social accounts which displayed negative sentiment such as disgust and anger was a response to content shared by anti-social accounts.

This research argues for future research to extend on the findings around anonymity, it would be advantageous to conduct research that measures different trigger events, taking in account the level to which content such as Islamophobia, extremism, misinformation and disinformation has been mainstreamed. This would allow for the development of the theoretical ideas around the dynamic shift of the role of anonymity proposed by the present research. This research also recommends the development of soft verification to tackle online anonymity. Although the present findings found that anonymity was not crucial in perpetuating the disseminations of harmful content during Covid-19, nevertheless a large amount of previous research (Awan et al., 2019; Christopherson, 2007; Sutch and Carter, 2019;) has well documented the role in which anonymity can play in the spread of harmful content online. Therefore, it is suggested that whilst further investigations are made into looking at how the dynamics around the role of anonymity may be changing, it is crucial in the meantime that this is not overlooked when employing tactics to reduce and mitigate the spread of harmful behaviour and content online.

References

Akçakaya, A. (2021) Problems of Healthcare Professionals in COVID-19 Pandemic. Available at: http://hdl.handle.net/20.500.12645/28477 [Accessed 11th June 2020].

Al-Astewani, A. (2021) To open or close? COVID-19, Mosques and the role of religious authority within the British Muslim community: A socio-legal analysis. *Religions*, *12*(1), p.11. Available at: https://doi.org/10.3390/rel12010011

Ali, I. (2020) Impacts of rumors and conspiracy theories surrounding COVID-19 on preparedness programs. *Disaster Medicine and Public Health Preparedness*, pp.1-6. Available at: https://doi.org/10.1017/dmp.2020.325

Amichai-Hamburger, Y., Kingsbury, M. and Schneider, B.H. (2013) Friendship: An old concept with a new meaning?. *Computers in Human Behavior*, *29*(1), pp.33-39. Available at: https://doi.org/10.1016/j.chb.2012.05.025

Andersen, K.G., Rambaut, A., Lipkin, W.I., Holmes, E.C. and Garry, R.F. (2020) The proximal origin of SARS-CoV-2. *Nature medicine*, *26*(4), pp.450-452. Available at: https://doi.org/10.1038/s41591-020-0820-9

Anthony, L. (2004) *AntConc: A learner and classroom friendly, multi-platform corpus analysis toolkit.* Available at: https://www.researchgate.net/profile/Laurence_Anthony/publication/267631346_Proceedings_of_IWLeL_2004_An_Interactive_Workshop_on_Language_E-learning_2004/links/5458cd870cf26d5090acf212/Proceedings-of-IWLeL-2004-An-Interactive-Workshop-on-Language-E-learning-2004.pdf#page=7 [Accessed 12th June 2020].

Anthony, L. (2018). AntConc (Version 3.5.7) [Computer Software]. Tokyo, Japan: Waseda University. Available at: https://www.laurenceanthony.net/software [Accessed 11th June 2020].

Apuke, O.D. and Omar, B. (2021) Fake news and COVID-19: modelling the predictors of fake news sharing among social media users. *Telematics and Informatics*, *56*, p.101475. Available at: https://doi.org/10.1016/j.tele.2020.101475

Awan, I., Sutch, H., and Carter, P. (2019) Extremism Online - Analysis of extremist material on social media in: Commission for Countering Extremism: Presentation & Discussion of Academic Research, 1/5/19, London, UK. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/834369/Awan-Sutch-Carter-Extremism-Online.pdf [Accessed 12th June 2020].

Awan, I. (2014) 'Islamophobia on Twitter: A Typology of Online Hate Against Muslims on Social Media' Policy & Internet 6 (2): 133-150. Available at: https://doi.org/10.1002/1944-2866.POI364

Awan, I. and Zempi, I. (2015) 'I Will Blow Your Face OFF'—Virtual and Physical World Anti-Muslim Hate Crime, *The British Journal of Criminology*, Volume 57, Issue 2, 1 March 2017, Pages 362–380. Available at: https://doi.org/10.1093/bjc/azv122

Baker, P. (2018). Language, sexuality and corpus linguistics. Journal of Language and Sexuality, 7(2), 263-279. Available at: https://doi.org/10.1075/jls.17018.bak

Baker, P., Gabrielatos, C., & McEnery, T. (2013). Sketching Muslims: A corpus driven analysis of representations around the word 'Muslim'in the British press 1998–2009. *Applied linguistics*, *34*(3), 255-278. Available at: https://doi.org/10.1093/applin/ams048

Bakry, M., Syatar, A., Haq, I., Mundzir, C., Arif, M. and Amiruddin, M.M. (2020) Arguing Islamophobia during COVID-19 Outbreaks: A Consideration Using Khuṣūṣ Al-

Balwā. *International Journal of Criminology and Sociology*, *9*, pp.2757-2765. Available at: https://doi.org/10.6000/1929-4409.2020.09.340

Barberá, P. (2020) Social media, echo chambers, and political polarization. *Social Media and Democracy: The State of the Field, Prospects for Reform, 34*. Available at: http://pablobarbera.com/static/echo-chambers.pdf [Accessed 12th June 2020].

Berman, G. (2009) Anti-social behaviour order statistics. *Standard Note: SN/SG/3112, London: House of Commons Library*. Available at: https://researchbriefings.files.parliament.uk/documents/SN03112/SN03112.pdf [Accessed 12th June 2020].

Bi, S. (2020) Racialisation of Rescuehood: Contextualising British Muslims stuck abroad during COVID-19 pandemic. Available at: https://d1wqtxts1xzle7.cloudfront.net/62755724/Racialisation_of_Rescuehood__Contextualising_British_Muslims_stuck_abroad_during_COVID-19_pandemic_20200402-40429-owpgnu-with-cover-page-v2.pdf?Expires=1639489885&Signature=JkH-dWhTUzejdasxQkQxvolj55tt6AtPV43P6pQ5LrdKZjiPKUFedrsPRBEYoXl564O-tKV3H4h9c35WGBfmxeNseKzw8xfBi5mqYFcI6LC9wM0K3-kAchqFQf0UZRfuXOWY6oMALDsX7ej5xIMO9w1gGDDqu9cTYVsAQqzSLzWg5EmYLsa1YHbjJ5dOBYdQL4qmkHKAo9YHBLpERrx3JClyH5rD1d62OxQ-q5QM85pjdhC-qzwjQuDOW-R-CzngGAGZOOSX4JYZp9dAhNkvGbKGTp3J2ATVCbtBAThYmg4a1CCI9Dlbn~0jfwnA7Kqo8AKipt9X5nkgAryNTHwiiQ__&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA [Accessed 11th June 2020].

Challies, D.M., Hunt, M., Garry, M. and Harper, D.N. (2011) Whatever gave you that idea? False memories following equivalence training: A behavioral account of the misinformation effect. *Journal of the Experimental Analysis of Behavior*, *96*(3), pp.343-362. Available at: https://doi.org/10.1901/jeab.2011.96-343

Chakraborti, N. and Garland, J. (2009) Hate Crime, Sage: London.

Christopherson, K.M. (2007) The positive and negative implications of anonymity in Internet social interactions:“On the Internet, Nobody Knows You’re a Dog”. *Computers in Human Behavior*, *23*(6), pp.3038-3056. Available at: https://doi.org/10.1016/j.chb.2006.09.001

Cinelli, M., Morales, G.D.F., Galeazzi, A., Quattrociocchi, W. and Starnini, M. (2021) The echo chamber effect on social media. *Proceedings of the National Academy of Sciences*, *118*(9). Available at: https://doi.org/10.1073/pnas.2023301118

Cinnirella, M. and Green, B. (2007) Does ‘cyber-conformity’vary cross-culturally? Exploring the effect of culture and communication medium on social conformity. *Computers in Human Behavior*, *23*(4), pp.2011-2025. Available at: https://doi.org/10.1016/j.chb.2006.02.009

Compton, J. (2013). “Inoculation theory,” in The SAGE Handbook of Persuasion: Developments in Theory and Practice, 2nd Edn, eds J. P. Dillard and L. Shen (Thousand Oaks, CA: SAGE Publications), 220–236.

Craker, N., & March, E. (2016). The dark side of Facebook®: The Dark Tetrad, negative social potency, and trolling behaviours. *Personality and Individual Differences*, *102*, 79-84. Available at: https://doi.org/10.1016/j.paid.2016.06.043

Crossley, S. A., Kyle, K., & McNamara, D. S. (2017). Sentiment Analysis and Social Cognition Engine (SEANCE): An automatic tool for sentiment, social cognition, and social-order analysis. Behavior research methods, 49(3), 803-821. Available at: https://doi.org/10.3758/s13428-016-0743-z

Digital, Culture, Media and Sport Committee (2019) Disinformation and ‘fake news’: Final Report. Available at:

https://publications.parliament.uk/pa/cm201719/cmselect/cmcumeds/1791/1791.pdf [Accessed 10th December 2021].

Dearden, L (2020) ‘Coronavirus: “Dangerous” Conspiracy Theories Could Spark Wave of Islamophobic Attacks When Lockdown Lifts, Report Warns’. *Independent*, 19 April. Available at: https://www.independent.co.uk/news/uk/home- news/coronavirus-muslim-lockdown-conspiracy-theories-tommy-robinson-katie- hopkins-a9471516.html [Accessed 10th June 2020].

Del Vicario, M., Vivaldo, G., Bessi, A., Zollo, F., Scala, A., Caldarelli, G. and Quattrociocchi, W. (2016) Echo chambers: Emotional contagion and group polarization on facebook. *Scientific reports*, *6*(1), pp.1-12. Available at: https://doi.org/10.1038/srep37825

Edwards, A., Webb, H., Housley, W., Beneito-Montagut, R., Procter, R. and Jirotka, M. (2021) Forecasting the governance of harmful social media communications: findings from the digital wildfire policy Delphi. *Policing and society*, *31*(1), pp.1-19. Available at: https://doi.org/10.1080/10439463.2020.1839073

Ellis-Peterson, H & Rahman, A.S. (2020) Coronavirus conspiracy theories targeting Muslims spread in India. Theguardian, 13 April. Available at: https://www.theguardian.com/world/2020/apr/13/coronavirus-conspiracy-theories-targeting-muslims-spread-in-india [Accessed 10th June 2020].

Falade, B.A. and Coultas, C.J. (2017) Scientific and non-scientific information in the uptake of health information: The case of Ebola. *South African Journal of Science, 113*(7-8), pp.1-8. Available at: http://dx.doi.org/10.17159/sajs.2017/20160359

Festinger, L. Pepitone, A. and Newcomb, T. (1952) Some consequences of de-individuation in a group. *The Journal of Abnormal and Social Psychology*, *47*(2, Suppl), pp.382-389. Available at: doi: 10.1037/h0057906

Freeman, D., Waite, F., Rosebrock, L., Petit, A., Causier, C., East, A., Jenner, L., Teale, A.L., Carr, L., Mulhall, S. and Bold, E. (2020) Coronavirus conspiracy beliefs, mistrust, and compliance with government guidelines in England. *Psychological medicine*, pp.1-13. Available at: doi: 10.1017/S0033291720001890

Gampa, A., Wojcik, S.P., Motyl, M., Nosek, B.A. and Ditto, P.H. (2019) (Ideo)logical reasoning: Ideology impairs sound reasoning. *Social Psychological and Personality Science*, *10*(8), pp.1075-1083. Available at: https://doi.org/10.1177/194855061982905

Goodboy, A. K., & Martin, M. M. (2015). The personality profile of a cyberbully: Examining the Dark Triad. *Computers in human behavior*, *49*, 1-4. Available at: https://doi.org/10.1016/j.chb.2015.02.052

Gruzd, A., & Roy, J. (2014). Investigating political polarization on Twitter: A Canadian perspective. *Policy & Internet*, *6*(1), 28-45. Available at: https://doi.org/10.1002/1944-2866.POI354

Gruzd, A., Wellman, B., and Takhteyev, Y. (2011). Imagining Twitter as an imagined community. American Behavioral Scientist, 55(10), 1294-1318. Available at: https://doi.org/10.1177/0002764211409378

Hamill-Stewart, C. (2020) Coronavirus pandemic being exploited to fuel Islamophobia. Arab news, 8 September. Available at: https://www.arabnews.com/node/1655056/world [Accessed 12th June 2020].

Haber, E. M. (2015). On the Stability of Online Language Features: How Much Text do you Need to know a Person?. arXiv preprint arXiv:1504.06391. Available at: https://doi.org/10.48550/arXiv.1504.06391

Hiltunen, T., McVeigh, J., & Säily, T. (2017). How to turn linguistic data into evidence? Studies in Variation, Contacts and Change in English, 19. Available at: https://d1wqtxts1xzle7.cloudfront.net/57552746/hiltunen_et_al_2017-libre.pdf?1539369191=&response-content-disposition=inline%3B+filename%3DHow_to_turn_linguistic_data_into_evidenc.pdf&Expir

es=1663711870&Signature=LrKbMjAQ0w8wit~oGAU6rntmVagtkjx-3OthK29hvab0fn2not2jrySkchneVD3B1vII~5dGF1d3XpMfHCS2h67STCppFN~QWOf5PAJavzPaMa8HXqMzfeEucvAf8pI7zwPgfP6mymCc8hOCOuZMOa6aPRxUK2upxm~70dIzDkyyqRuNEGXhcFNPplLUIimkD2dY99m~pEzTkuiGSOVfXngtqdYkBYi34j~O3qCx7~PeWPz3V48z09QKjPKDzOD1JKEHWGaybq7wznfqoeCf01bYKC6pzCAPmJwMBxrXZJh2v1wScGXodVJwvVTvXuXKkKEb8Fy9yZTSueOeKJ6TXQ__&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA [Accessed 10th June 2020].

HM Government, (2011) *Prevent Strategy* Presented to Parliament by the Prime Minister and the Secretary of State for the Home Department by Command of Her Majesty. Available at: http://www.homeoffice.gov.uk/publications/counter-terrorism/prevent/prevent-strategy/prevent-strategy-review?view=Binary [Accessed 18th May 2022].

Jadhav, S. (2020) Covid-19, Muslim Community and Indian Media. *National Journal on……*, p.40. Available at: https://snmorcollege.org.in/research_journal/social_issues_problems_vol_9_issue_2.pdf#page=47 [Accessed 11th June 2020].

Jaspal, R. and Lopes, B. (2021) Discrimination and mental health outcomes in British Black and South Asian people during the COVID-19 outbreak in the UK. *Mental Health, Religion & Culture*, *24*(1), pp.80-96. Available at: https://doi.org/10.1080/13674676.2020.1871328

Jerard, J. (2019) Online Extremism: Agents of Disruption in the Digital Age. Available at: https://www.rsis.edu.sg/wp-content/uploads/2019/08/CO19170.pdf [Accessed 11th December 2021].

Kane, G. C., Alavi, M., Labianca, G., & Borgatti, S. P. (2014). What's different about social media networks? A framework and research agenda. *MIS quarterly, 38*(1), 275-304. Available at: https://www.jstor.org/stable/26554878 [Accessed 11th December 2021].

Klausen, J., Marks, C.E. and Zaman, T. (2018) Finding extremists in online social networks. *Operations Research*, *66*(4), pp.957-976. Available at: https://doi.org/10.1287/opre.2018.1719

Lapidot-Lefler, N. and Barak, A. (2015) The benign online disinhibition effect: Could situational factors induce self-disclosure and prosocial behaviors?. *Cyberpsychology: Journal of Psychosocial Research on Cyberspace*, *9*(2). Available at: https://doi.org/10.5817/CP2015-2-3

Lavorgna, A. and Myles, H. (2021) Science denial and medical misinformation in pandemic times: A psycho-criminological analysis. *European Journal of Criminology*, p.1477370820988832. Available at: https://doi.org/10.1177/1477370820988832

Lee, E.J. (2006) When and how does depersonalization increase conformity to group norms in computer-mediated communication?. *communication research*, *33*(6), pp.423-447. Available at: https://doi.org/10.1177/0093650206293248

Li, H.O.Y., Bailey, A., Huynh, D. and Chan, J. (2020) YouTube as a source of information on COVID-19: a pandemic of misinformation?. *BMJ global health*, *5*(5), p.e002604. Available at: http://dx.doi.org/10.1136/bmjgh-2020-002604

Lin, Y. (2021) Ten Internet Statistics very marketer should know in 2021. Available at: https://www.oberlo.co.uk/blog/internet-statistics [Accessed 10th December 2021].

Maertens, R., Anseel, F. and van der Linden, S. (2020) Combatting climate change misinformation: Evidence for longevity of inoculation and consensus messaging effects. *Journal of Environmental Psychology*, *70*, p.101455 Available at: https://doi.org/10.1016/j.jenvp.2020.101455

Martel, C., Pennycook, G. and Rand, D.G. (2020) Reliance on emotion promotes belief in fake news. *Cognitive research: principles and implications*, *5*(1), pp.1-20 Available at: https://doi.org/10.1186/s41235-020-00252-3

McEnery, T., & Hardie, A. (2011). Corpus linguistics: Method, theory and practice. Cambridge University Press.

Mitchell, A., and Oliphant, J. B. (2020) *Americans Immersed in COVID-19 News; Most Think Media Are Doing Fairly Well Covering It. Pew Research Center.* Available at: https://www.journalism.org/2020/03/18/americans-immersed-in-covid-19-news-most-think-media-are-doing-fairly-well-covering-it/ [Accessed 18th March 2020].

Mohammad, S. M., & Turney, P. D. (2013). Crowdsourcing a word–emotion association lexicon. Computational intelligence, 29(3), 436-465. Available at: https://doi.org/10.1111/j.1467-8640.2012.00460.x

Moscovici, S. and Zavalloni, M. (1969) The group as a polarizer of attitudes. *Journal of personality and social psychology*, *12*(2), p.125. Available at: https://doi.org/10.1037/h0027568

Mukherjee, S. (2020) Disparities, desperation, and divisiveness: Coping with COVID-19 in India. *Psychological Trauma: Theory, Research, Practice, and Policy*, *12*(6), p.582. doi:10.1037/tra0000682

Nagar, I. and Gill, S. (2020) Head is where the herd is: Fake news and effect of online social conformity on Islamophobia in Indians. Available at: https://doi.org/10.1037/tra0000682

Nouh, M., Nurse, J.R. and Goldsmith, M. (2019) Understanding the radical mind: Identifying signals to detect extremist content on twitter. In *2019 IEEE International Conference on Intelligence and Security Informatics (ISI)* (pp. 98-103). IEEE. Available at: doi: 10.1109/ISI.2019.8823548

Ofcom (2020) *Half of UK Adults Exposed to False Claims about Coronavirus.* Available at: https://www.ofcom.org.uk/about-ofcom/latest/features-and-news/half-of-uk-adults-exposed-to-false-claims-about-coronavirus [Accessed 18th May 2020].

Online harms (2019) Online Harms white paper. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/973939/Online_Harms_White_Paper_V2.pdf [Accessed 12th June 2020].

Orpin, D. (2005). Corpus linguistics and critical discourse analysis: Examining the ideology of sleaze. International journal of corpus linguistics, 10(1), 37-61. Available at: https://doi.org/10.1075/ijcl.10.1.03orp

Padilla-Walker, L.M. and Carlo, G. eds. (2015) *Prosocial development: A multidimensional approach*. Oxford University Press.

Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis. Foundations and Trends® in Information Retrieval, 2(1–2), 1-135. Available at: http://dx.doi.org/10.1561/1500000011

Pantazi, M., Kissine, M. and Klein, O. (2018) The power of the truth bias: False information affects memory and judgment even in the absence of distraction. *Social cognition*, *36*(2), pp.167-198. Available at: https://doi.org/10.1521/soco.2018.36.2.167

Peddinti, S. T., Ross, K. W., & Cappos, J. (2017). Mining Anonymity: Identifying Sensitive Accounts on Twitter. *arXiv preprint arXiv:1702.00164*. Available at: https://arxiv.org/pdf/1702.00164.pdf [Accessed 18th May 2020].

Pennycook, G., McPhetres, J., Zhang, Y., Lu, J.G. and Rand, D.G. (2020) Fighting COVID-19 misinformation on social media: Experimental evidence for a scalable accuracy-nudge intervention. *Psychological science*, *31*(7), pp.770-780. Available at: https://doi.org/10.1177/0956797620939054

Pepitone, A. and Newcomb, T. (1952) Some consequences of de-individuation in a group. *The Journal of Abnormal and Social Psychology*, *47*(2, Suppl), pp.382-389. Available at : doi:10.1037/h0057906

Perrigo, B. (2020) It was already dangerous to be Muslim in India. Then came the coronavirus. Available at: https://time.com/5815264/coronavirus-india-islamophobia-coronajihad/ [Accessed 11TH June 2020].

Pourghomi, P., Dordevic, M. and Safieddine, F. (2018) The Spreading of Misinformation online: 3D Simulation. In *2018 5th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE)* (pp. 299-304). IEEE. Available at: doi: 10.1109/ICITACEE.2018.8576937

Prasad, A. (2020) The organization of ideological discourse in times of unexpected crisis: Explaining how COVID-19 is exploited by populist leaders. *Leadership*, *16*(3), pp.294-302. Available at: https://doi.org/10.1177/1742715020926783

Scott, M. (1997) PC analysis of key words—and key key words. *System*, *25*(2), 233-245. Available at: https://doi.org/10.1016/S0346-251X(97)00011-0

Schwarz, N., Newman, E. and Leach, W. (2016) Making the truth stick and the myths fade: Lessons from cognitive psychology. Behavioural Science and Policy, 2, 85–95. Available at: https://my.vanderbilt.edu/tnprekevaluation/files/2017/06/Pre_k-Review-BSP_vol2no1-2016.pdf#page=95 [Accessed 11th June 2020].

Skagerberg, E.M. and Wright, D.B. (2008) The prevalence of co-witnesses and co-witness discussions in real eyewitnesses. *Psychology, Crime & Law*, *14*(6), pp.513-521. Available at: https://doi.org/10.1080/10683160801948980

Sotlar, A. (2004). Some Problems with a Definition and Perception of Extremism within a Society. *Policing in central and Eastern Europe: Dilemmas of contemporary criminal justice*, 703-707. Available at: https://www.ojp.gov/pdffiles1/nij/Mesko/208033.pdf [Accessed 11th June 2020].

Spring, M. (2020) The casualties of this year's viral conspiracy theories. BBC news, 26 December, Available at: https://www.bbc.co.uk/news/blogs-trending-55355911. [Accessed 19th May 2020].

Staun, J. ed. (2008) *Radicalisation, recruitment and the EU counter-radicalisation strategy*. COT Institute for Safety, Security and Crisis Management.

Stroud, N. J. (2010). Polarization and partisan selective exposure. *Journal of communication*, *60*(3), 556-576. Available at: https://doi.org/10.1111/j.1460-2466.2010.01497.x

Suler, J. (2004) The online disinhibition effect. *Cyberpsychology & behavior*, *7*(3), pp.321-326. available at: https://doi.org/10.1089/1094931041291295

Sutch, H. and Carter, P. (2019) Anonymity, Membership-Length and Postage Frequency as Predictors of Extremist Language and Behaviour among Twitter Users. *International Journal of Cyber Criminology*, *13*(2), pp.439-459. Available at: https://www.cybercrimejournal.com/SutchCarterVol13Issue2IJCC2019.pdf [Accessed 11th June 2020].

The Crime and Disorder Act (1998). *The Crime and Disorder Act 1998.* Available at: https://www.legislation.gov.uk/ukpga/1998/37/contents [Accessed 12th June 2020].

Udupa, S. (2020) Decoloniality and Extreme Speech. Available at: https://drive.google.com/file/d/1ohqSQrcw9JMtrldflInn5pG1Gk-OUURh/view [Accessed 12th June 2020].

Uscinski, J.E., Enders, A.M., Klofstad, C., Seelig, M., Funchion, J., Everett, C., Wuchty, S., Premaratne, K. and Murthi, M. (2020) Why do people believe COVID-19 conspiracy theories?. *Harvard Kennedy School Misinformation Review*, *1*(3). Available at: https://misinforeview.hks.harvard.edu/article/why-do-people-believe-covid-19-conspiracy-theories/ [Accessed 12th June 2020].

Van Der Linden, S., Roozenbeek, J. and Compton, J. (2020) Inoculating against fake news about COVID-19. *Frontiers in psychology, 11*, p.2928. Available at: https://doi.org/10.3389/fpsyg.2020.566790

Williams, M.L. and Burnap, P. (2016) Cyberhate on social media in the aftermath of Woolwich: A case study in computational criminology and big data. *British Journal of Criminology*, *56*(2), pp.211-238. Available at: https://doi.org/10.1093/bjc/azv059

Wojcieszak, M. (2010) ‘Don’t talk to me’: Effects of ideologically homogeneous online groups and politically dissimilar offline ties on extremism. *New Media & Society*, *12*(4), pp.637-655. Available at: https://doi.org/10.1177/1461444809342775

World Health Organization (2020) *Novel Coronavirus (2019-nCoV) Situation Report - 13.* Available at: https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200202-sitrep-13-ncov-v3.pdf [Accessed 2nd February 2020].

Zarocostas, J. (2020) How to fight an infodemic. *The lancet*, *395*(10225), p.676. Available at: https://doi.org/10.1016/S0140-6736(20)30461-X

Zimbardo, P.G. (1969) The human choice: Individuation, reason, and order versus deindividuation, impulse, and chaos. In *Nebraska symposium on motivation*. University of Nebraska press.

TABLES TO INSERT

TABLE 1: Categories for Comparison

Category	Anonymity	Postage Frequency	Membership Length
Low	5-7 identifiable items	Average number of tweets per day between zero and ten	0 to 1000 days active
Moderate	3-4 identifiable items	Average number of tweets per day between 11 and 50	1001 to 3000 days active
High	0- 2 identifiable items	Average number of tweets per day between 51 and 150	3001 to 5001 days active

TABLE 2

Keyness analysis for low Anonymity and suggested extreme words

	Low Anonymity comparisons					
	Low anonymity vs Moderate anonymity			Low anonymity vs High anonymity		
Key terms	Frequency value	Keyness value	Significance value	Frequency value	Keyness value	Significance value
muslimban	54	+113.3	<.0003	54	+103.58	<.0003
beingmuslimterriost	44	+92.32	<.0002	44	+113.01	<.0002
islamspreadcovid	40	+83.93	<.0002	40	+102.74	<.0002
delhiagainstjehadviolence	30	+62.94	<.0001	30	+77.05	<.0001
banjihadimedia	23	+48.26	<.0001	23	+59.07	<.0001
ihateislam	21	+44.06	<.0001	21	+53.94	<.0001
stayawayfromislam	1	-30.45	<.0001	-	-	-
bantablighijamal	-	-	-	11	+28.25	<.0001
islamiccoronajehad	-	-	-	2	-29.88	<.0001
jihadagent	-	-	-	-	-	-
jihadwatchrs	2	-30.36	<.0001	-	-	-
islamistheproblem	-	-	-	-	-	-

crushtablighispitters	-	-	-	-	-	-
islamicvirus	-	-	-	-	-	-
islamiscancer	-	-	-	-	-	-
islamisevil	-	-	-	-	-	-
coronajehad	-	-	-	-	-	-
allahisgay	-	-	-	-	-	-
coronahoax	-	-	-	-	-	-
coronajihad	-	-	-	-	-	-
covidiots	-	-	-	-	-	-
covidscam	-	-	-	-	-	-
radicalislamicterrorist	-	-	-	-	-	-
nizamuddinidiots	-	-	-	-	-	-
saynotohalal	-	-	-	45	+115.58	<.0002
banjahiljamat	-	-	-	-	-	-
islamexposed	-	-	-	-	-	-
spitting	-	-	-	5	-26.15	<.0001

TABLE 3

Keyness analysis for Moderate Anonymity and suggested extreme words

	Moderate Anonymity comparisons					
	Moderate anonymity vs Low anonymity			Moderate anonymity vs High anonymity		
Key terms	Frequency value	Keyness value	Significance value	Frequency value	Keyness value	Significance value
muslimban	-	-	-	-	-	-
beingmuslimterriost	-	-	-	-	-	-
islamspreadcovid	-	-	-	-	-	-
delhiagainstjehadviolence	-	-	-	-	-	-
banjihadimedia	-	-	-	-	-	-
ihateislam	-	-	-	-	-	-
stayawayfromislam	44	+30.45	<.0001	44	+77.34	<.0001
bantablighijamal	-	-	-	-	-	-
islamiccoronajehad	-	-	-	6	-40.08	<.0001
jihadagent	-	-	-	35	+61.52	<.0001
jihadwatchrs	50	+30.36	<.0001	50	+63.66	<.0001
islamistheproblem	-	-	-	21	+36.91	<.0001
crushtablighispitters	-	-	-	1	-31.2	<.0001
islamicvirus	-	-	-	1	-25.12	<.0001

islamiscancer	-	-	-	37	+65.03	<.0001
islamisevil	-	-	-	-	-	-
coronajehad	-	-	-	-	-	-
allahisgay	-	-	-	-	-	-
coronahoax	37	+31.91	<.0001	-	-	-
coronajihad	-	-	-	-	-	-
covidiots	-	-	-	-	-	-
covidscam	110	+94.87	<.0003	110	+193.35	<.0003
radicalislamicterrorist	49	+42.26	<.0001	49	+86.13	<.0001
nizamuddinidiots	-	-	-	-	-	-
saynotohalal	-	-	-	-	-	-
banjahiljamat	-	-	-	-	-	-
islamexposed	-	-	-	-	-	
spitting	-	-	-	-	-	-

TABLE 4

Keyness analysis for High Anonymity and suggested extreme words

	High Anonymity comparisons					
	High anonymity vs Low anonymity			High anonymity vs moderate anonymity		
Key terms	Frequency value	Keyness value	Significance value	Frequency value	Keyness value	Significance value
muslimban	6	-103.58	<.0001	-	-	-
beingmuslimterriost	-	-	-	-	-	-
islamspreadcovid	-	-	-	-	-	-
delhiagainstjehadviolence	-	-	-	-	-	-
banjihadimedia	-	-	-	-	-	-
ihateislam	-	-	-	-	-	-
stayawayfromislam	-	-	-	-	-	-
bantablighijamal	-	-	-	-	-	-
islamiccoronajehad	66	+29.88	<.0001	66	+40.08	<.0001
jihadagent	-	-	-			
jihadwatchrs	-	-	-	4	-63.66	<.0001
islamistheproblem	-	-	-			

crushtablighispitters	-	-	-	36	+31.2	<.0001
islamicvirus	-	-	-	30	+25.12	<.0001
islamiscancer	-	-	-	58	+62.25	<.0001
islamisevil	53	+34.36	<.0001	-	-	-
coronajehad	-	-	-	38	+40.78	<.0001
allahisgay	-	-	-	37	+39.71	<.0001
coronahoax	-	-	-	-	-	-
coronajihad	-	-	-	-	-	-
covidiots	-	-	-	-	-	-
covidscam	-	-	-	-	-	-
radicalislamicterrorist	-	-	-	-	-	-
nizamuddinidiots	-	-	-	-	-	-
saynotohalal	-	-	-	-	-	-
banjahiljamat	-	-	-	-	-	-
islamexposed	-	-	-	-	-	-
spitting	79	+26.15	<.0001	-	-	-

TABLE 5

Keyness analysis for low membership length and suggested extreme words

	Low Membership length comparisons					
	Low membership length vs Moderate membership length			Low membership length vs High membership length		
Key terms	Frequency value	Keyness value	Significance value	Frequency value	Keyness value	Significance value
muslimban	6	-44.92	<.0001	-	-	-
beingmuslimterriost	-	-	-	-	-	-
islamspreadcovid	-	-	-	-	-	-
delhiagainstjehadviolence	-	-	-	-	-	-
banjihadimedia	-	-	-	-	-	-
ihateislam	21	+28.27	<.0001	-	-	-
stayawayfromislam	-	-	-	2	-89.68	<.0001
bantablighijamal	-	-	-	-	-	-
islamiccoronajehad	16	-27.05	<.0001	-	-	-
jihadagent	-	-	-	-	-	-
jihadwatchrs	-	-	-	8	-63.85	<.0001
islamistheproblem	-	-	-	-	-	-

crushtablighispitters	-	-	-	-	-	-
islamicvirus	-	-	-	-	-	-
islamiscancer	60	+80.77	<.0001	-	-	-
islamisevil	62	+83.47	<.0001	62	+43.56	<.0001
coronajehad	-	-	-			
allahisgay	37	+49.81	<.0001	37	+26	<.0001
coronahoax	37	+49.81	<.0001	37	+26	<.0001
coronajihad	9	-34.18	<.0001	-	-	-
covidiots	-	-	-	9	-33.4	<.0001
covidscam	-	-	-	-	-	-
radicalislamicterrorist	-	-	-	-	-	-
nizamuddinidiots	2	-67.93	<.0001	-	-	-
saynotohalal	-	-	-	-	-	-
banjahiljamat	5	-50.81	<.0001	-	-	-
islamexposed	51	+60.2	<.0001	51	+35.83	<.0001
spitting	-	-	-	-	-	-

TABLE 6

Keyness analysis for moderate membership length and suggested extreme words

	Moderate Membership length comparisons					
	Moderate membership length vs Low membership length			Moderate membership length vs High membership length		
Key terms	Frequency value	Keyness value	Significance value	Frequency value	Keyness value	Significance value
muslimban	53	+44.92	<.0001	53	+30.94	<.0001
beingmuslimterriost	44	+62.8	<.0001	44	+31.99	<.0001
islamspreadcovid	40	+57.09	<.0001	40	+29.08	<.0001
delhiagainstjehadviolence	30	+42.82	<.0001	-	-	-
banjihadimedia	23	+32.83	<.0001	-	-	-
ihateislam	-	-	-	-	-	-
stayawayfromislam	-	-	-	-	-	-
bantablighijamal	-	-	-	-	-	-
islamiccoronajehad	58	+27.05	<.0001	58	+42.16	<.0001
jihadagent	35	+49.95	<.0001	35	+25.44	<.0001
jihadwatchrs	-	-	-	6	-68.01	<.0001
islamistheproblem	-	-	-	-	-	-

crushtablighispitters	39	+55.66	<.0001	39	+28.35	<.0001
islamicvirus	-	-	-	-	-	-
islamiscancer	-	-	-	-	-	-
islamisevil	-	-	-	-	-	-
coronajehad	-	-	-	-	-	-
allahisgay	-	-	-	-	-	-
coronahoax	-	-	-	-	-	-
coronajihad	51	+34.18	<.0001	51	+37.07	<.0001
covidiots	-	-	-	3	-49.02	<.0001
covidscam	-	-	-	-	-	-
radicalislamicterrorist	49	+69.93	<.0001	49	+35.62	<.0001
nizamuddinidiots	58	+67.93	<.0001	58	+42.16	<.0001
saynotohalal	45	+64.23	<.0001	45	+32.17	<.0001
banjahiljamat	55	+50.81	<.0001	55	+39.98	<.0001
islamexposed	1	-60.2	<.0001	-	-	-
spitting	-	-	-	60	+35.79	<.0001

TABLE 7

Keyness analysis for high membership length and suggested extreme words

	High Membership length comparisons					
	High membership length vs Low membership length			High membership length vs moderate membership length		
Key terms	Frequency value	Keyness value	Significance value	Frequency value	Keyness value	Significance value
muslimban	-	-	-	1	-30.94	<.0001
beingmuslimterriost	-	-	-	-	-	-
islamspreadcovid	-	-	-	-	-	-
delhiagainstjehadviolence	-	-	-	-	-	-
banjihadimedia	-	-	-	-	-	-
ihateislam	-	-	-	-	-	-
stayawayfromislam	43	+89.68	<.0002	43	+102.2	<.0002
bantablighijamal	-	-	-	-	-	-
islamiccoronajehad	-	-	-	-	-	-
jihadagent	-	-	-	-	-	
jihadwatchrs	42	+63.85	<.0002	42	+68.01	<.0002
islamistheproblem	-	-	-	-	-	-

crushtablighispitters	-	-	-	-	-	-
islamicvirus	-	-	-	-	-	-
islamiscancer	-	-	-	-	-	-
islamisevil	-	-	-	-	-	-
coronajehad	-	-	-	-	-	-
allahisgay	-	-	-	-	-	-
coronahoax	-	-	-	-	-	-
coronajihad	-	-	-	-	-	-
covidiots	28	+33.4	<.0001	28	+49.02	<.0001
covidscam	-	-	-	-	-	-
radicalislamicterrorist	-	-	-	-	-	-
nizamuddinidiots	-	-	-	-	-	-
saynotohalal	-	-	-	-	-	-
banjahiljamat	-	-	-	-	-	-
islamexposed	-	-	-	-	-	-
Spitting	-	-	-	1	-35.79	<.0001

TABLE 8

Keyness analysis for low postage frequency and suggested extreme words

	Low postage frequency comparisons					
	Low postage frequency vs moderate postage frequency			Low postage frequency vs high postage frequency		
Key terms	Frequency value	Keyness value	Significance value	Frequency value	Keyness value	Significance value
muslimban	6	-62	<.0001	-	-	-
beingmuslimterriost	44	+47.44	<.0001	-	-	-
islamspreadcovid	40	+43.12	<.0001	-	-	-
delhiagainstjehadviolence	30	+32.34	<.0001	-	-	-
banjihadimedia	-	-	-	-	-	-
ihateislam	-	-	-	-	-	-
stayawayfromislam	44	+39.6	<.0001	-	-	-
bantablighijamal	-	-	-	-	-	-
islamiccoronajehad	74	+79.78	<0001	-	-	-
jihadagent	-	-	-	-	-	-
jihadwatchrs	9	-42.62	<.0001	-	-	-

islamistheproblem	-	-	-	-	-	-
crushtablighispitters	39	+42.05	<.0001	-	-	-
islamicvirus	32	+34.5	<.0001	-	-	-
islamiscancer	64	+69	<.0001	-	-	-
islamisevil	62	+66.84	<.0001	-	-	-
coronajehad	38	+40.97	<.0001	-	-	-
allahisgay	37	+39.89	<.0001	-	-	-
coronahoax	37	+39.89	<.0001	-	-	-
coronajihad	-	-	-	-	-	-
covidiots	-	-	-	-	-	-
covidscam	110	+118.59	<.0002	-	-	-
radicalislamicterrorist	-	-	-	-	-	-
nizamuddinidiots	60	+64.69	<.0001	-	-	-
saynotohalal	45	+48.51	<.0001	-	-	-
banjahiljamat	60	+64.69	<.0001	-	-	-
islamexposed	52	+56.06	<.0001	-	-	-
spitting	90	+46.75	<.0001	-	-	-

TABLE 9

Keyness analysis for moderate postage frequency and suggested extreme words

	Moderate postage frequency comparisons					
	Moderate postage frequency vs low postage frequency			Moderate postage frequency vs high postage frequency		
Key terms	Frequency value	Keyness value	Significance value	Frequency value	Keyness value	Significance value
muslimban	54	+62	<.0001	-	-	-
beingmuslimterriost	-	-	-	-	-	-
islamspreadcovid	-	-	-	-	-	-
delhiagainstjehadviolence	-	-	-	-	-	-
banjihadimedia	-	-	-	-	-	-
ihateislam	-	-	-	-	-	-
stayawayfromislam	1	-39.6	<.0001	-	-	-
bantablighijamal	-	-	-	-	-	-
islamiccoronajehad	-	-	-	-	-	-
jihadagent	35	+61.28	<.0001	-	-	-
jihadwatchrs	47	+42.62	<.0001	-	-	-

islamistheproblem	-	-	-	-	-	-
crushtablighispitters	-	-	-	-	-	-
islamicvirus	-	-	-	-	-	-
islamiscancer	-	-	-	-	-	-
islamisevil	-	-	-	-	-	-
coronajehad	-	-	-	-	-	-
allahisgay	-	-	-	-	-	-
coronahoax	1	-38.56	<.0001	-	-	-
coronajihad	-	-	-	-	-	-
covidiots	-	-	-	-	-	-
covidscam	-	-	-	-	-	-
radicalislamicterrorist	49	+85.79	<.0001	-	-	-
nizamuddinidiots	-	-	-	-	-	-
saynotohalal	-	-	-	-	-	-
banjahiljamat	-	-	-	-	-	-
islamexposed	-	-	-	-	-	-
spitting	11	-46.75	<.0001	-	-	-

TABLE 10

Keyness analysis for high postage frequency and suggested extreme words

	High postage frequency comparisons					
	High postage frequency vs low postage frequency			High postage frequency vs moderate postage frequency		
Key terms	Frequency value	Keyness value	Significance value	Frequency value	Keyness value	Significance value
muslimban	-	-	-	-	-	-
beingmuslimterriost	-	-	-	-	-	-
islamspreadcovid	-	-	-	-	-	-
delhiagainstjehadviolence	-	-	-	-	-	-
banjihadimedia	-	-	-	-	-	-
ihateislam	-	-	-	-	-	-
stayawayfromislam	-	-	-	-	-	-
bantablighijamal	-	-	-	-	-	-
islamiccoronajehad	-	-	-	-	-	-
jihadagent	-	-	-	-	-	-
jihadwatchrs	-	-	-	-	-	-
islamistheproblem	-	-	-	-	-	-

crushtablighispitters	-	-	-	-	-	-
islamicvirus	-	-	-	-	-	-
islamiscancer	-	-	-	-	-	-
islamisevil	-	-	-	-	-	-
coronajehad	-	-	-	-	-	-
allahisgay	-	-	-	-	-	-
coronahoax	-	-	-	-	-	-
coronajihad	-	-	-	-	-	-
covidiots	-	-	-	-	-	-
covidscam	-	-	-	-	-	-
radicalislamicterrorist	-	-	-	-	-	-
nizamuddinidiots	-	-	-	-	-	-
saynotohalal	-	-	-	-	-	-
banjahiljamat	-	-	-	-	-	-
islamexposed	-	-	-	-	-	-
spitting	-	-	-	-	-	-

TABLE 11

Table 11: Mean and SD EmoLex Scores for Prosocial and Antisocial Tweets

	Condition	N	Mean	Std. Deviation
Anger	Prosocial	18495	.026	.043
	Antisocial	21845	.019	.043
Anticipation	Prosocial	18495	.023	.042
	Antisocial	21845	.025	.055
Disgust	Prosocial	18495	.015	.035
	Antisocial	21845	.014	.039
Fear	Prosocial	18495	.032	.049
	Antisocial	21845	.024	.048
Joy	Prosocial	18495	.016	.039
	Antisocial	21845	.020	.053
Sadness	Prosocial	18495	.022	.038
	Antisocial	21845	.019	.044
Surprise	Prosocial	18495	.011	.031
	Antisocial	21845	.014	.041
Trust	Prosocial	18495	.044	.066
	Antisocial	21845	.041	.069