Crossing the line: abuse of footballers on Twitter during the 2020 Men's European Football Championship

<u>Table of Contents</u>

Content warning

This dissertation repeats highly offensive words and phrases in full, as is common practice in the study of hate speech. Specifically, pages 40 and 47 contain text from offensive tweets that are overtly racist and homophobic in nature. Please read these passages at your own discretion.

Ethical statement

The data used in this dissertation was collected from Twitter using its Filtered Stream API (see Section 3.1). Only public-facing tweets were collected. Where individual tweets are presented in this document, the author's name and Twitter handle have been omitted to protect their identity.

Code, images, and data

All code used is available on GitHub at: https://github.com/dbckz/crossing-the-line

High-resolution, interactive versions of the figures featured in this dissertation are available at: https://dbckz.github.io/crossing-the-line

All tweet data collected is available on Google Drive at:

https://drive.google.com/drive/folders/1rJL2Pww7eVXdNTC1D25oGCCcmL8t9O2v?usp=sharing

Abstract

There have been numerous reports of footballers being targeted with hateful messages on social media in recent years, and there is evidence from studies in the English Premier League that black players from the most prominent teams are most targeted. For this dissertation, the online abuse of footballers was analysed on the international stage, through a comprehensive study of hateful speech directed at footballers on Twitter during the 2020 Men's European Football Championship. Tweets aimed at the players of Belgium, England, France, Germany, Scotland, and the Netherlands were collected over a 27 day period. Two methods were used to classify tweets as hateful: a search of key terms from the Hatebase catalogue, and the application of the machine learning-based Perspective API. The latter was found to be more accurate on all fronts, achieving greater precision and recall.

Descriptive analysis of the final found it to be a major flashpoint for online abuse. The three England players that missed penalties - Bukayo Saka, Marcus Rashdord, and Jadon Sancho, all of whom are of ethnicities other than white - were the players most targeted with hateful tweets in the aftermath of the final, with ethnic slurs the most prominent type of slur observed in those tweets. Furthermore, each player was targeted with an additional wave of hateful tweets when they themselves tweeted about their experience in the days following the final. There were 1,739 hateful tweets directed at the three players in the five days after the final, 77% of all hateful tweets in this period. The analysis thus quantifies the scale of the abuse received by Saka, Rashford, and Sancho, providing empirical evidence that supports the many anecdotal media reports of such abuse that were published following the final.

Separately, a statistical model was built to analyse the factors associated with a player receiving hateful tweets throughout the whole tournament. A regression analysis found a strong association between a player losing a match or missing a penalty and them being targeted with hateful tweets. Additionally, a positive association was found between a player being of an ethnicity other than white and them being targeted with hateful tweets. Importantly, this last finding remained true when matches involving penalties (including the

final) were excluded, suggesting that a player’s ethnicity was a causal factor in them receiving a higher number of hateful tweets. Although racist incidents in stadia have significantly reduced in recent decades, this finding suggests that racist attitudes amongst football supporters persist, and that social media is providing a new medium through which such attitudes can be expressed.

List of figures

List of tables

1. Introduction

As the clock neared 11pm on the evening of 11th July 2021, 19 year-old Arsenal forward Bukayo Saka stepped forward to take a decisive penalty for England in the final of the men's European Football Championship, needing to score to keep England in the contest. Italian goalkeeper Gianluigi Donnarumma dived to his left to save Saka's strike, sending Italian fans into rapture, and prolonging England's 55 year long wait for an international trophy. As a heartbroken Saka was consoled by his teammates on the Wembley pitch, a darker story was unfolding on social media as Saka, and teammates Marcus Rashford and Jadon Sancho, who had also missed penalties, were subjected to a torrent of racist abuse on Twitter and Instagram (Lyons, 2021).

The targeting of these England players is just one example from a long list of racist incidents that have dogged the sport in recent years, both in stadia and online. In October 2019, a qualifying match for the European Championships between Bulgaria and England in Sofia was halted in the 28th minute as a group of Bulgarian fans directed monkey chants and Nazi salutes toward England's Tyrone Mings, Raheem Sterling, and Marcus Rashford - the three black players in England's starting XI that night (Britton, 2019). Sterling and midfielder Jude Bellingham received similar treatment during a recent match against Hungary in Budapest, England's first competitive game since their final defeat to Italy. Hungarian supporters directed monkey chants at the two players, and hurled projectiles at Sterling after he scored the opening goal of the game (Hayes, 2021).

Racism in football is not an issue isolated to Eastern Europe, nor is it only fans who are the culprits. In December 2020, the players of Paris Saint-Germain and İstanbul Başakşehir walked off the pitch in protest after the fourth official directed a racial slur at Başakşehir assistant Pierre Webo (Shread, 2020). In 2011, former Chelsea and England captain John Terry was accused of racially abusing Queens Park Rangers defender Anton Ferdinand during a Premier League fixture (Fifield, 2011). Terry was acquitted in a criminal trial, but received a four-match ban from the English Football Association (FA) and a £220,000 fine - the equivalent of just over a week of Terry's wages.

In recent years, social media platforms have provided a new medium through which supporters can engage in conversation about football-related news and events. The presence of many footballers on these platforms has opened up new paths of communication via which supporters can engage directly with players. Such communication can be beneficial, helping foster a greater connection between supporters and players. Moreover, players have leveraged their status on these platforms for altruistic purposes, a prime example being Manchester United forward Marcus Rashford's use of Twitter to orchestrate a campaign to provide free school meals to impoverished children in the UK during the Covid-19 pandemic (Kleinman, 2020). However, the direct access to players enabled through social media can also be used to target them with hateful and abusive messages. Research commissioned by the Professional Footballers Association (PFA) Charity during the 2019/20 Premier League season found that dozens of players from Black, Asian, or minority ethnic (BAME) backgrounds were routinely targeted with racist abuse on social media (Professional Footballers Association Charity, 2020).

Online abuse is not limited to racism however. Arsenal players Bernd Leno and Granit Xhaka have spoken openly about their experiences, Leno once receiving a message telling him to 'do it like Enke' (in reference to German goalkeeper Robert Enke, who died by suicide in 2009) (Cotterill and Kerai, 2021), and Xhaka receiving death threats against his wife and daughter (Lawton and Joyce, 2019). Online abuse has also been seen in the women's game. Former England international turned sports journalist Karen Carney was forced to delete her Twitter account after she received a barrage of sexist abuse triggered by a tweet from the official account of Leeds United FC that mocked her punditry (Mercer, 2021).

There have been several quantitative studies into online abuse of footballers in the domestic game, but none analysing international competition. This dissertation begins to address this gap, and studies the targeted abuse of footballers on Twitter during the 2020 Men's European Football Championship. The research aims to answer the following research questions:

RQ1: Which players receive the most abuse on Twitter during the tournament?

RQ2: Is a player's ethnicity indicative of the volume of abuse they are targeted with?

RQ3: What other factors are associated with a player receiving a larger volume of hateful tweets?

Data is collected from Twitter using its Filtered Stream API, with tweets mentioning or replying to the players from six teams captured for a 27 day period during the tournament. Previous studies of online hate in football have applied either a key-term search or a machine learning-based methodology to identify hateful messages. In this study, both methods are applied, and are evaluated in order to answer an auxiliary research question:

RQ4: Is a key-term search or machine learning-based approach more effective for identifying hateful, football-related tweets?

After classifying the tweets, analytic methods are applied to explore RQ1-3.

The dissertation is divided into four sections. Firstly, a review of the literature is presented in Section 2, charting the history of racism in European football, and exploring the role of social media in facilitating the proliferation of racist and hateful views in the online world. This review informs six hypotheses, which are presented in Section 2.4. Secondly, the methodology for testing these hypotheses is outlined in Section 3, which details the data collection process and the analytical methods employed. Thirdly, the findings from the analysis are presented in Section 4. Finally, implications of the research and areas for future work are discussed in Section 5.

2. Literature Review

2.1 Racism in European football

The issue of racism in European football has a long and complex history, and its ongoing manifestation today can only be understood by considering both broader societal attitudes and the football-specific context. On the latter, Doidge (2016, p.176) emphasises the importance of distinguishing between two distinct ways that racism presents itself in football. Firstly, racism may originate from “ideologically motivated and politically driven” fans, which Doidge terms *instrumental* racism. Amongst such fans may be members of far-right groups who use football as a vehicle to promote their ideologies. Secondly, racism can originate from fans responding to events on the pitch with racist words or chants that denigrate rival players, which Doidge terms *organic* racism - racism that is not ideologically driven, but stems from a desire from fans to create an advantage for their team by diminishing their opponent. Despite this difference in motivation, both instrumental and organic racism can be equally damaging to the players subjected to it.

There is evidence that racist incidents inside stadia have decreased in recent years. In the UK, annual arrest figures related to such incidents continue to reduce year-on-year (Home Office, 2020). However, Burdsey (2011) argues that this has created an exaggerated sense of progress in tackling the issue of racism in football. In reality, significant structural challenges remain. Although European teams have become more ethnically diverse, football remains a white institution: “games are watched by crowds of predominantly white supporters, controlled by white match officials, and teams are run by white (male) managers, coaches, owners and directors” (Burdsey, 2011, p.5). Indeed, in 2020 just six of the ninety-two English football league clubs had a manager from a BAME background, despite over a quarter of Premier League players coming from such a background (Kelsey, 2020). Cashmore and Cleland (2011) found that 56% of fans believe this underrepresentation stems from institutional racism at the executive level of the game. This is an important finding, as it shows that those within the game see institutional racism as a significant issue.

Burdsey's argument that there has been an overly optimistic sense of progress in tackling racism in football is evidenced by the international governing body FIFA's 2016 decision to disband its anti-racism task force after just three years because it had "completely fulfilled its mission" (Harris, 2016). During the football season that followed, anti-discrimination foundation Kick It Out received more reports of racist abuse than ever before (Conn, 2017). For Burdsey (2007) and Cashmore and Cleland (2011), FIFA's decision is indicative of a desire by the footballing authorities to sustain the game's white hegemonic power structure. Furthermore, Burdsey (2007, p.9) argues that the common narrative that football is 'colour-blind' toward racial inequality is actually a means for maintaining these power structures. A 'colour-blind' director can always justify selecting a white man as head coach over a BAME candidate by saying they have the greater skills or experience. A supporter that racially abuses a player can always be blamed as being part of an ignorant minority. Doidge (2016) argues that such actions subtly reinforce institutionally racist aspects of football's power structure. Football thus embodies Bonilla-Silva's (2001, p.12) observations that although overt expressions of racism may have decreased, white privilege is instead "accomplished through institutional, subtle, and non-racial means".

The issue of racism in European football also needs to be culturally understood. Patterns of migration have differed across the continent, with multiculturalism first becoming prevalent in Western Europe due to the colonial history of many of these nations. Doidge (2017, pp.174-177) observes that as the demographic makeup of European nations has altered with migration, so too has the composition of football teams. Globalisation and the accompanying influx of money into European football through television deals and sponsorship packages has enabled teams to scout talent from across the world, and thus domestic and international teams have become increasingly diverse. English football in particular has been transformed by globalisation, and issues of racism have abounded in a country still coming to terms with its colonial past.

England was the first country in which football was professionalised in the decades after the establishment of the Football Association (FA) in 1863. Those who played and followed the sport were overwhelmingly white and working class, and this remained the status quo until the late 1970s when a number of British-born black footballers emerged as prominent figures in top flight English football (Cleland and Cashmore, 2014, p.639). Certain factions of the predominantly white supporter base did not welcome the success of these players - they were routinely abused in football stadia by supporters singing racist chants, making monkey noises, and throwing bananas at them (Back et al., 2001; Garland and Rowe, 2001). As globalisation brought more foreign players into the country, the FA wanted to appeal to a more global audience, which led to the creation of the Premier League in 1992. Today, the league is the most watched in the world, and is home to more foreign players than any other league (Sky Sports, 2017).

Cleland and Cashmore (2014) argue that this internationalisation of English football clubs has created a perception of declining racism in English football which may not be fully justified. Anti-racism initiatives in English football have been driven by the Kick It Out foundation, who have made significant impact in reducing overt racism in stadia through the installation of prescriptive codes of conduct which fans have to adhere to or risk being ejected and possibly banned from stadia (Cleland and Cashmore, 2014). Although there have been campaigns in other European countries that have been similarly successful - such as the Never Again Association in Poland, and the club-oriented *fanprojekte* in Germany (Doidge, 2016, pp.175-182) - overt racism in stadia remains a problem across much of the continent. Italian football is a prominent example, with racist chanting aimed at BAME players a regular occurence (Deveau and Hellier, 2020; Giuffrida, 2019). However, even in countries such as the UK where overt racism in stadia has been largely reduced, issues of racism remain in the wider game.

Kilvington and Price (2019) describe how racism in football plays out in the twenty-first century by drawing on Goffman's (1959) dramaturgical metaphor of human social interaction, which distinguishes between *frontstage* and *backstage* performance. Goffman posits that individuals present antithetical versions of themselves in public (the frontstage) and in private (the backstage). Through this model, it can be seen that the decrease in overt racism in stadia may not necessarily be indicative of a reduction in racist attitudes, but rather their retreat from the frontstage to the backstage. This is supported by Cleland and Cashmore (2014, p.644) who find that racism has been “left below the surface where it has simmered away” with “racist undertones...still there and very much alive”. Kilvington and Price (2019, p.66) argue that today a new medium is providing a platform for backstage racism to be projected frontstage: social media.

2.2 Hate speech on social media

The rise of digital technologies has created a new paradigm for human communication, enabling messages to be sent and received from almost any location in the world in near-real time. Social media platforms mediate a huge amount of this global conversation; Twitter, for example, reports an average of 192 million active users each day (Twitter, 2021, p.2). Much of the conversation on social media is public-facing, providing researchers a new means by which to monitor and track public attitudes and debates in the *frontstage* (Chaudhry, 2015).

Social media platforms can also be used by individuals to broadcast discriminatory views or direct targeted abuse at individuals they otherwise would be unable to communicate with. Sunstein (2017) argues that algorithmically-driven content recommendation systems employed by social media platforms can have a polarizing effect by acting to create echo chambers that galvanize attitudes and emotions, which may promulgate negative expression toward minority groups. Although critics of this echo chamber discourse argue that it does not stand up to empirical scrutiny (Guess et al., 2018), it is at the very least evident that the internet and social media have augmented public discourse, and provided new communication pathways via which harm and abuse can be delivered.

There is no commonly agreed definition of hate speech. Nockleby (2000) defines it as “any communication that disparages a person or a group based on some characteristics such as race, color, ethnicity, gender, sexual orientation, nationality, race, or other characteristics”. Gerstenfeld (2017) argues that motivation for hate speech is not necessarily to do with the individual victim, but rather the victim’s “outgroup” status. Perry (2001) adds that the aim of a hate crime is often to send a message to the wider “outgroup” community that they are expected to behave according to expectations set by the “ingroup”. Thus hate speech can be viewed as a weapon used by the privileged majority to secure their position of domination in society (Nakayama, 2017).

According to Douglas et al. (2005), motivations for online hate are similar to those for offline hate - rarely is it driven by a hatred of the individual, but rather the “outgroup” they represent. Concretely, perpetrators choose their targets based on their perceived belonging to a group with particular characteristics such as gender, race, religion, sexual orientation, or political persuasion. Cleland (2014, p.415) identifies the particular example of nationalist sentiment flourishing on social media by “rejecting multiculturalism...through the presentation of whiteness and national belonging and an outright hostility and resistance toward the Other”. Whilst motivations for online hate may be the same as those driving offline hate, there are properties of social media platforms that may enable such hate speech to flourish.

Crandall and Eshleman (2003, p.421) argue that individuals are more likely to discriminate against others when the target is remote than they are in face-to-face situations. This is manifest in the online world, where social media facilitates previously non-existent lines of communication between aggressors and would-be victims, which Nakayama (2017) argues makes individuals more willing to post abusive messages online than they would be to espouse discriminatory or hateful speech in public spaces. Moreover, the low barrier to entry for those wishing to express an opinion on social media means that it may be perceived as a democratic space, legitimising fringe or offensive views (Nakayama, 2017, p.70).

Suler (2004) argues that this “online disinhibition effect” arises primarily from properties of social media networks. Firstly, social media enables a veil of *anonymity* that allows people to separate their online and offline identities, freeing them from the moral and psychological constraints that would ordinarily moderate their behaviour. Secondly, the *invisibility* of the abused to the abuser means that the latter may not fully appreciate the extent of the harm being experienced by the former. Taken together, these two factors create a reduced sense of responsibility in the abuser, leading to increased online hate that aggravates the harm caused to victims. An empirical analysis by Correa et al. (2015) found evidence of the disinhibition effect on social media sites Twitter and Whisper, with Whisper users presenting a more acute disinhibition complex due to the greater level of anonymity the platform affords users relative to that of Twitter.

One of the largest studies of online hate was conducted by the Anti-Defamation League (2016), which explored antisemitic hate on Twitter. Using a broad set of keywords, the ADL identified 2.6 million tweets containing antisemitic language during a one year period from August 2015 to July 2016. The report highlights three main findings. Firstly, over 800 journalists received antisemitic abuse, with the top ten most-targeted accounting for 83% of the total abuse. This indicates that whilst hateful language is widespread, there are a small number of individuals who are likely to be disproportionately targeted. Secondly, there was an uptick in antisemitic tweets during the period of the 2016 US presidential campaign, and the report argues that campaign-related news events in the offline world triggered waves of antisemitic abuse in the online world. This is evidenced by a temporal analysis that relates spikes in antisemitic tweets to specific campaign events, mostly related to then-Republican nominee Donald Trump. Thirdly, the report highlights that journalist Jonathan Weisman was met with a second, larger wave of abuse when he posted his own tweet sharing details of the previous abuse he had received. The report concludes that those who speak out will likely suffer further abuse, that may be even more severe.

More recently, the spread of Covid-19 has been accompanied by a rise in prejudice against East Asians after the virus was first identified in Wuhan, China in late 2019. Tahmasbi et al. (2021) conducted a cross-platform analysis on Twitter and 4chan's */pol* message board, demonstrating an increase in Sinophobic language on both platforms during the early months of the pandemic. In a large-scale study of over 600 million tweets collected between February and April 2020, the company Moonshot identified 193,000 tweets containing conspiracy theories, hate speech, or incitements to violence related to Covid-19 (Moonshot, 2020). This shows that when analysing hateful speech online, it may be important to consider both the proportion and absolute number of messages that are hateful. Although only ~0.03% of the tweets were flagged, such a large number of harmful tweets still has significant potential to cause damage.

This analysis also identified a 300% increase in tweets encouraging violence against China during a single week of March 2020, a time at which many countries in Europe and America were entering their first lockdowns. This increase in East Asian prejudice on social media is unsurprising, given there was an increase in offline hate crimes directed at East Asian individuals during the early months of the pandemic (Whitehead, 2020), and the prevalence of anti-Chinese rhetoric from high-profile figures in the West such as President Trump (Reja, 2021). A result that is perhaps less expected comes from a later analysis by Moonshot, which identified a significant increase in antisemitic language on social media during the pandemic, much of it associated with vaccine conspiracy theories. This reinforces the ADL's findings discussed previously: just as the 2016 US election served as a vehicle for antisemitism, so has the pandemic. This suggests that a major event like the European Football Championship could also act as a vehicle for abuse.

2.3 Social media abuse of sports personalities

The relationships between sports clubs, athletes, and fans has changed significantly in recent decades. Whilst mass media has brought unprecedented popularity and money into professional sport, the recent growth of social media has facilitated a level of interaction between clubs, athletes, and fans that is arguably of more profound consequence. Today, social media augments the experience of consuming sport, providing a platform for supporters to debate refereeing decisions, consume real-time in-game updates, and receive breaking news about the sports they follow (Gibbs et al., 2014).

For clubs, social media has become a place for brand management and public relations (Price et al., 2013). Social media is attractive to clubs because it is easy to use, bypasses the traditional media, and has global reach (Price et al., 2013, p.448). Social media, and Twitter in particular, has become the predominant space in which sports news breaks, and is the primary forum for sports fans to express their opinions about such news (Sanderson and Truax, 2014).

For athletes, social media not only facilitates brand management, but can enable what Frederick et al. (2012) call a “digital closeness” between fans and athletes. Athletes see this as a major draw of social media platforms, as expressed by a former Premier League footballer, writing under pseudonym:

> “Twitter and such like…have brought back the sense of connection between footballers and fans that for so long was held up by journalists as an example of the ‘you and them’ scenario that developed when money began to flood into the game and, in turn, players’ wages increased out of all proportion with the man in the street” (The Secret Footballer, 2011)

In addition to using social media as a tool to connect with fans, Browning and Sanderson (2012) find that athletes engage with social media “to see what is being said about them as they *are* the conversation”. Just as supporters in a stadium can respond to a team’s performance by cheering or booing the players, supporters online can use social media to praise or abuse players. However, the scale of the latter can be orders of magnitude larger, with opinions expressed by potentially millions of fans worldwide, not just the tens of thousands in a stadium. Moreover, Bennett and Jönsson (2017, p.210) highlight that the type of abuse received on social media is often worse in content than that received through other media, as it facilitates much more directed and expletive-laden messages. The challenge of social media abuse is thus one of both scale and severity. Kilvington and Price (2019, p.74) summarise the core tradeoff for athletes in using social media: whilst it can be a “beneficial communicative tool”, it also brings challenges due to “the ease with which fans can attack them”.

Kick It Out first received reports of discrimination taking place on social media during the 2012/13 season (Kick It Out, 2020). The number of reports has continued to increase season-on-season up until the most recent one, with Kick It Out attributing the decrease during the 2019/20 season to greater awareness amongst players of the mechanisms available for reporting abuse directly to social media companies. Awareness of the issue primarily stems from these survey-based reports, players speaking out, and investigative journalism. There are fewer examples of quantitative studies, with those that do exist focusing on the English Premier League.

A 2015 study by social media analytics firm Brandwatch was the first to reveal the scale of abuse of footballers on social media (Brandwatch, 2015). Proprietary software was used to identify abuse aimed at Premier League footballers during the 2014/15 season, finding that players from Chelsea, Liverpool, Arsenal, Manchester United, and Manchester City were the most targeted. These are five of the so-called “Big Six” major English football teams, suggesting that the popularity of a team is indicative of the level of abuse that players receive. The five most targeted players were all Black and received large amounts of racist abuse, and all played for the aforementioned clubs. Liverpool striker Mario Balotelli was by far the most targeted player, receiving almost eight times as much abuse as second-ranked Danny Welbeck of Arsenal. This supports the ADL’s finding that when a group is the target of abuse, a few individuals within the group will receive a disproportionate volume of the abuse.

In 2020, the Professional Footballers' Association Charity in England commissioned a quantitative study of online abuse of footballers during 'Project Restart' - the six-week period commencing on 17th June during which the remaining fixtures of the 2019/20 English football league season were played following a pandemic-induced three month hiatus. Project Restart took place against the backdrop of heightened public conversation around racism triggered by the murder of George Floyd by a police officer in Minneapolis in May 2020. In response to this event, and in solidarity with the global protests in support of the Black Lives Matter movement that followed, Premier League players took a knee prior to kick-off during all 92 Project Restart fixtures.

The PFA study used machine learning techniques to analyse 825,515 Twitter posts involving 44 high-profile players and ex-players, and concludes with three main findings: targeted abuse of footballers on social media has become normalised; speaking up can create negative repercussions for players; and social media platforms have blindspots that fail victims of abuse (Professional Footballers Association Charity, 2020). The first of these findings confirms the scale of the problem identified previously by Brandwatch, and shows that social media has enabled racist expressions to be projected very much into the frontstage. Although the majority of the abusive tweets were racist, the study also identified sexist, antisemitic, and transphobic hate speech. The second finding resonates with Jonathan Weisman's experience of antisemitic abuse. In this case, the three most targeted players - Raheem Sterling, Wilfried Zaha, and Adebayo Akinfenwa - all "spoke out about specific incidents, and within the next 48 hours received a sudden spike in direct attention, completely dwarfing what is normal for each player". These three players accounted for 50% of all abusive tweets identified, in concurrence with previous findings that a disproportionate amount of abuse will be experienced by a few individuals. The third finding points to the challenge social media companies face when trying to moderate content. The study identified that 29% of the racially abusive posts came in emoji form, and were not deleted for many months, despite being flagged by users as offensive. More recent research has found that content moderation tools employed by social media platforms remain poor at identifying emoji-based hate speech (Kirk et al., 2021). It is therefore vital that this study accounts for the presence of emoji-based hate.

2.4 Hypotheses

The preceding literature review shows that racism remains a significant problem in European football, and that social media is providing a new medium through which footballers may be abused. Whilst there have been several quantitative studies into the abuse of footballers on social media, these have all focused on domestic competition, particularly the English Premier League. This thesis aims to address this gap by studying the phenomenon during the 2020 Men's European Football Championship, played during the summer of 2021 having been delayed a year due to the Covid-19 pandemic. Informed by the literature review, six hypotheses are outlined below.

Previous studies by the PFA and Brandwatch on the online abuse of Premier League footballers have shown that players from high-profile clubs are likely to receive the most abuse, and that the majority of online abuse aimed at footballers is racist in nature, and largely aimed at BAME players. From these findings, the following hypotheses are proposed:

- **H1:** players will receive more abuse if they play for a high-profile club domestically.
- **H2:** players of ethnicities other than white will receive the larger volume of hateful tweets.

As demonstrated in the ADL's research, offline events often trigger waves of online abuse. Previous examples of players being subject to online abuse have mostly stemmed from their participation in matches where their team has lost, especially where a player is perceived to have significantly contributed to the defeat. Chelsea striker Tammy Abraham received racist abuse on Twitter after missing a decisive penalty in the club's defeat to Liverpool in the 2019 UEFA Super Cup (PA Media, 2019); Arsenal forward Nicolas Pépé was targeted after being sent off during a 0-0 draw against Leeds United in November 2020 (Collings, 2020); and Manchester City's Raheem Sterling and Kyle Walker were victims of online abuse following their defeat to Chelsea in the 2021 Champions League final (Church, 2021). Taking these examples into consideration, the following hypotheses are proposed:

- **H3:** abuse will be greater if a player's team loses the match.
- **H4:** abuse will be greater if a player misses a penalty.
- **H5:** abuse will be greater if a player receives a red card.

Finally, research from Brandwatch, the PFA, and the ADL finds that those receiving the most abuse are disproportionately targeted. The PFA's research found that 50% of abusive tweets identified were aimed at 3 of the 44 players studied (Professional Footballers Association Charity, 2020, p.1). Based on this result, and given this study looks at 118 players (see 3.1.1), the following hypothesis is proposed:

- **H6:** of all abuse identified, greater than 50% of it will be targeted at 10 players or fewer

The next section describes the methodology used to test these hypotheses.

3. Methodology

This study was conducted using data collected during the UEFA Men's European Football Championship taking place between the 11th June and 11th July 2021. Twitter was chosen as the medium of study as it is almost universally used by clubs and players (Professional Footballers Association Charity, 2020); indeed, all 24 national teams competing in the tournament were found to have a verified Twitter account. Moreover, Twitter has become a primary location for interactions between fans, clubs, players, ex-players, pundits, and sports journalists (Price et al., 2013; Rivers and Ross, 2019), and numerous players have publicly reported receiving abuse on the platform in the past twelve months (de Menezes, 2020; MacInnes, 2021; Mercer, 2021).

3.1 Data collection

3.1.1 Use of the Twitter Filtered Stream API

Data was collected from Twitter using its Filtered Stream Application Programming Interface (API) (Twitter Developer Platform, 2021). This enables tweet data (and associated metadata) to be collected according to filter rules specified by the user. For example, a simple filter rule could specify that only tweets containing a particular hashtag are collected. The API provides data in near-real time, meaning that the resulting dataset contains tweets that may subsequently have been deleted. This is important for accurately measuring the volume of abusive tweets that were sent, as it means tweets deleted by the author, or through Twitter's content moderation process, are still captured.

The players of the national teams of Belgium, England, France, Germany, the Netherlands, and Scotland were chosen as the subjects of the study. With the exception of Scotland, these teams were chosen as they had a relatively even mix of white players and players of ethnicities other than white, relative to the other teams in the tournament.[1] This provides greater statistical power for testing H2. Scotland was included due to their involvement in a high-profile group stage match against England, where the decision of both teams to take

[1] Note that the categorisation of a player's ethnicity as white or other than white was a subjective decision based on the author's best judgement.

the knee before kickoff was the focus of significant media attention (Kilpatrick, 2021; Taylor, 2021). Furthermore, a large proportion of these players have Twitter accounts, whereas many of the players from the lower-ranked and/or Eastern European teams do not.

Having selected the teams to study, the Twitter accounts of the players in each team's 26-man squad were identified. The accounts of 38 of these players could not be identified, resulting in a final list of 118 players (listed in Appendix A). Tweets replying to or mentioning each Twitter handle were collected. To simplify the analysis, only English-language tweets were collected. Data was collected between 19th June 2021 and 16th July 2021. This covered group stage matches, the round of sixteen, quarter-finals, semi-finals, and final, and there were 16 games involving the selected teams during this period (listed in Appendix B). Unfortunately, due to the large volume of tweets consumed in the aftermath of the final between England and Italy, a Twitter-imposed limit was reached at 12:37pm UTC on 12th July. No data was collected until this was resolved at 2:55pm UTC the same day.

For each tweet, the following metadata was collected in addition to the text of the tweet itself: tweet creation time, geolocation, user ID of the original poster (for replies), and the name, handle, bio, location, and public metrics (follower count, following count, tweet count) of the author and any other accounts mentioned in the tweet. Data was collected using a Python script leveraging the *requests* library to directly connect to the API.[2] This was based on a script provided by Twitter (twitterdev, 2021), which was modified to include additional logging and error handling, and apply the appropriate filter rules. The script was executed on a virtual machine running on the Google Cloud Platform. The API returns each tweet as a JavaScript Object Notation (JSON) object. The JSON data was written directly to text files, and the files were subsequently downloaded to a local machine for preprocessing and analysis. In total, 1,046,319 tweets were collected during the data collection period. Figure 1 shows the frequency of tweets during this period. The largest peak in activity was observed on the evening of 11th July, the night of the final.

[2] Data collection script: https://github.com/dbckz/crossing-the-line/blob/master/scripts/get_tweet_data.py

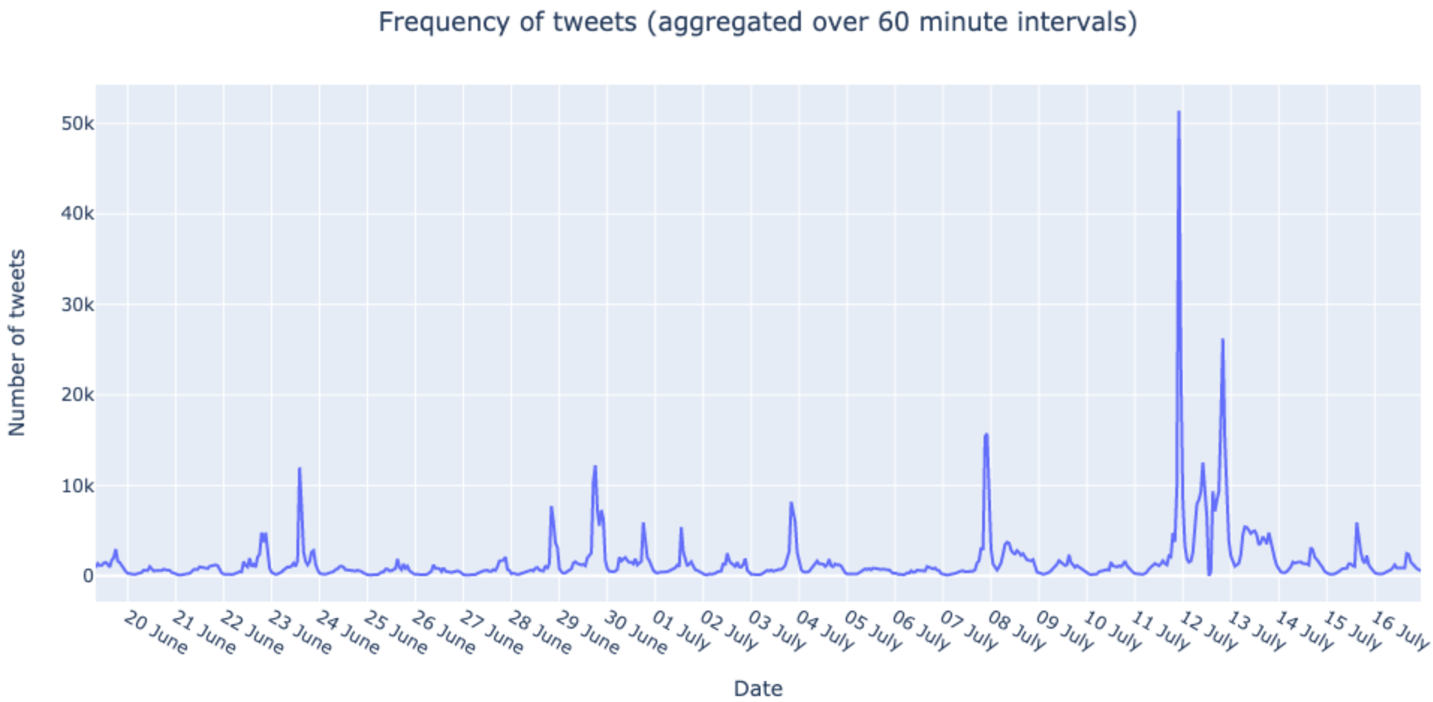

Figure 1: frequency of all tweets collected between 19th June and 16th July 2021, with tweets aggregated into 1 hour intervals. The largest peak occurs late on 11th July, following the conclusion of the final between England and Italy.

3.1.2 Preprocessing of tweet data

Preprocessing of the tweet data consisted of four steps. Firstly, a number of irrelevant fields were dropped from the tweet metadata, including like counts, retweet counts, and reply counts. These metrics served no purpose as they were all zero due to the fact tweet data was being collected in real time. Secondly, carriage returns, tabs, and new line returns were removed from the tweet text field, so that each tweet contained only a single line. This was a pragmatic step to simplify the subsequent data analysis. Thirdly, any duplicate rows were deleted, based on matching tweet IDs. Finally, the entire data structure was converted from hierarchical JSON into a flat comma-separated values (CSV) table containing the following columns:

Column name	**Description**
tweet_id	Unique identifier for the tweet
created_at	Timestamp of when the tweet was posted

in_reply_to_user_id	Account ID of user tweet was a reply to
tweet_text	Text of the tweet
lang	Language of the tweet (all “en”)
accounts_mentioned	List of accounts mentioned in the tweet
geo_place_name	Geotagged location of where the tweet was sent from
author_id	Unique ID for the author’s account
author_name	Display name of the author
author_handle	Twitter handle of the author
author_bio	Bio of the author
author_location	Location of the author
author_account_created_at	Timestamp of when the author’s account was created
author_followers_count	Number of accounts following the author
author_following_count	Number of accounts the author is following
author_tweet_count	Number of tweets the author has posted

Whilst this was not strictly necessary (as the analysis could be driven directly from the JSON data), it helped simplify the data analysis code, and meant the data could be more easily viewed by loading the CSV into spreadsheet/database management software such as Google Docs.

3.2 Methods for analysis - identifying hateful tweets

Identifying a tweet as hateful is not a trivial task. Chaudhry (2015), in their survey of studies of racist abuse on Twitter, emphasises the need to consider the context as well as the content of each tweet. Whether a tweet should be considered abusive may depend on the characteristics of the author, who their tweet is directed at, and the purpose of the tweet, amongst other factors. An illustrative example of the importance of context is present in the report by the Professional Football Association Charity (2020), which found that banana and monkey emojis were prominently used as a form of racist abuse against black footballers. Read in isolation, a tweet of such an emoji would likely be deemed completely innocent. But when considering the context in which the emoji was used - namely, the player it was aimed at, the accompanying tweets aimed at the player, other tweets posted by the author, and offline events on the football pitch - the abusive nature of the tweet becomes apparent.

In addition to hateful speech being highly contextual, it is also often subjective. Different social norms and personal opinions mean individuals may have different thresholds for what they consider hateful speech. Moreover, Del Vigna et al. (2017) argue that hateful speech exists on a continuum, which they segregate into three categories: no hate, weak hate, and strong hate. However, where the lines should be drawn between these categories remains subjective. Given this subjectivity, Waseem et. al's (2017) definition of hateful speech as is adopted, as “[language] that is unambiguous in its potential to be abusive, for example language that contains racial or homophobic slurs”. With this definition, tweets containing profanities should not necessarily be classed as hateful. This is an important feature when considering responses to footballing events, where supporters' reactions are often emotional and profanity-laden, whilst not necessarily being hateful or abusive.

Broadly speaking, there are three methods for identifying abusive tweets in the literature: manual annotation (Guest et al., 2021), searching for key terms (Anti-Defamation League, 2016; Bartlett et al., 2014), and applying a machine learning classifier (Professional Footballers Association Charity, 2020; Vidgen et al., 2020). Manual annotation is likely to result in the greatest accuracy, but is impractical in this use case due to the large number of tweets. In contrast, a key term search is trivial to perform at scale, but is liable to lead to false positives since it makes no attempt to account for the context a term is being used in (Bartlett et al., 2014). Similarly, it is straightforward to apply a machine learning classifier to this volume of tweets, but an effective classifier should have greater context-awareness than a key term search and so identify abusive tweets with greater accuracy. However, models for identifying abuse are complex and time-consuming to build, and may inherit biases or blindspots from the data they are trained on (Mehrabi et al., 2019).

Given the tradeoffs and potential shortcomings of both a key term search and a machine learning classifier, both approaches are applied. The accuracy of the two approaches are then compared (see Section 3.2.3 and Section 4.1). This enables the effectiveness of both approaches for identifying abuse to be better understood, and also provides greater confidence in the findings where results corroborate.

3.2.1 Identifying tweets containing offensive slurs using Hatebase

The selection of which terms to use for a key term search is of critical importance, as it introduces a systemic bias into the research method (Bartlett et al., 2014, p.10). To manage this bias, I did not curate my own list of hateful terms, but used Hatebase - an established catalogue of crowd-sourced hateful terms (Hatebase, 2021).

Hatebase is the largest such catalogue in existence, and is continually updated to reflect the ever-changing vocabulary used by those disseminating hateful speech (Coldewey, 2019; Quinn, 2013). The catalogue is accessed via a simple API, which was used to download all English-language hate terms and associated metadata. 1556 results were returned on 26th June 2021. Results were written to a CSV file with columns for the term, its meaning when used in a hateful context, a score from 0-100 denoting the term's "average offensiveness", and booleans indicating whether the term is related to nationality, ethnicity, religion, gender, sexual orientation, disability, or class.[3] Based on our definition of hateful language, an approach similar to that of Silva et al. (2016) is followed, excluding all terms with an average offensiveness score of less than 90. This increases the probability that a tweet containing one or more of these terms meets our criterion for hateful speech as being "unambiguous in its potential to be abusive". The final list of terms contained 289 terms from Hatebase.

A Python script[4] was run against the dataset of tweets to search the text of each tweet for each of the offensive terms, with a regular expression employed to avoid the so-called

[3] This table can be viewed at: https://docs.google.com/spreadsheets/d/1LjtHItkEODE4Sj1EeBxrcBWVvoUQWu-7uf3Sgzfjk_k/edit?usp=sharing

[4] Available here: https://github.com/dbckz/crossing-the-line/blob/master/scripts/process_hatebase.py

Scunthorpe problem, where inoffensive words are erroneously flagged due to containing a substring that is an offensive term.[5] The script appended a column to the dataset containing the matching terms for each tweet. The script also appended columns indicating whether the tweet contained terms related to nationality, ethnicity, religion, gender, sexual orientation, disability, or class, or whether the tweet contained at least one of the potentially offensive emojis. Any tweet containing at least one term was considered hateful.

In addition to the Hatebase terms, tweets are searched for banana, monkey, and watermelon emojis, since these have been prominently used as a form of racist abuse against BAME footballers on Twitter (Professional Football Association Charity, 2020). The following emojis were included:

Name	**Emoji**
Banana	🍌
Monkey	🐒
Monkey face	🐵
Speak-no-evil monkey	🙊
Hear-no-evil monkey	🙉
See-no-evil monkey	🙈
Gorilla	🦍
Watermelon	🍉

To the pleasant surprise of the author, emojis can be directly used in Python code, and a short Python script was written to search all tweets for these eight emojis, and flag those containing such emojis as hateful.[6]

3.2.2 Identifying abusive tweets using Perspective

Rather than go through the time-consuming process of building a machine learning classifier, Google's Perspective API was leveraged, considered the best-in-class open source tool for

[5] Having grown up just 6 miles from Scunthorpe, the author was acutely aware of this problem
[6] Available here: https://github.com/dbckz/crossing-the-line/blob/master/scripts/process_emoji.py

detecting online hate speech (Google, 2021a). It is unlikely that I would have been able to develop a more performant model of my own in the given timeframe.

Perspective is accessed through a simple API. The text to be analysed is posted to the API, which returns a number of attributes each mapped to a score between 0 and 1 indicating the "likelihood that a reader would perceive the comment as containing the given attribute" (Google, 2021b). For example, a score of 0.9 for the IDENTITY_ATTACK attribute indicates a 90% chance that a reader would consider the tweet to be a negative or hateful comment targeting someone because of their identity. Based on our definition of hateful language, tweets were flagged as hateful if they scored above 0.9 for any of the following attributes (Google, 2021c):

Attribute name	Attribute description
SEVERE_TOXICITY	A very hateful, aggressive, disrespectful comment or otherwise very likely to make a user leave a discussion or give up on sharing their perspective. This attribute is much less sensitive to more mild forms of toxicity, such as comments that include positive uses of curse words.
IDENTITY_ATTACK	Negative or hateful comments targeting someone because of their identity.
THREAT	Describes an intention to inflict pain, injury, or violence against an individual or group.

One limitation of using the Perspective API is that it is rate-limited to one request per second. A Python script[7] was written to call the API for every tweet in the dataset, and write the results to a CSV file. It took 13 days for the script to process all 1,090,461 tweets.

[7] Available here: https://github.com/dbckz/crossing-the-line/blob/master/scripts/process_perspective.py

A second limitation is that Perspective failed to process 85,368 of the tweets, throwing an error. Almost all of these errors were due to Perspective not recognising the text in these tweets as valid English language. A manual inspection of a random sample of 500 of these tweets[8] identified none of these as unambiguously hateful. For the purposes of this analysis, all tweets not successfully analysed by Perspective were therefore assumed to not be hateful.

3.2.3 Evaluating the classification methods

A random sample of 500 tweets marked as hateful and 500 tweets marked as not hateful was taken, for both the Hatebase and Perspective methods. These 2,000 tweets were manually reviewed to determine false positive and false negative rates.

Only a relatively small number of tweets were found to contain emojis, so a manual review of all such tweets was performed to determine whether they were being used in a hateful manner. This enabled evaluation of the Hatebase and Perspective approaches' ability to detect emoji-based hate.

3.3 Methods for analysis - testing hypotheses

To test the hypotheses, tweets were first aggregated to create a table of observations for each player on each day, with the following fields:[9]

---

[8] Dataset available here:
https://docs.google.com/spreadsheets/d/1aHPRKQCcPSVYFZKy4lzJTojnpQvKqGrw22RaOmVfurg/edit?usp=sharing

[9] Table available here:
https://docs.google.com/spreadsheets/d/13udUJlqTYSZvTbWMptLHaYFJJ7Fr7RkEUPvzLKNLsZY/edit#gid=1793625346

Fields
Name
Date
Country
Club
Club Coefficient
Twitter Handle
Ethnicity (white, other than white)
Featured in game (yes, no)
Is a matchday (yes, no)
Result (win, lose, draw)
Opponent
Round
Red Card (yes, no)
Penalty Outcome (scored, did not take, missed)
Total daily tweets
Total daily tweets containing Hatebase slurs or emojis
Total daily tweets flagged by Perspective

The list of players from the six chosen national teams, their domestic clubs, match results, red cards, and penalty information were taken from the tournament's official website (UEFA, 2021a) and manually inserted into the table of observations. Twitter handles were obtained through a direct search on the platform, with the majority of players easily found due to their verified status and large following. For unverified accounts, an informed decision was made on whether an account was likely to belong to the footballer in question based on their follower count, the recency of their posts, and other indicators such as their handle being tagged by the official account of their national or domestic team. Domestic club coefficients were taken from UEFA's website respectively (UEFA, 2021b).[10] Any player whose domestic club was not featured in the UEFA rankings was allocated a coefficient of zero.

Given 118 players were tracked over 27 days, this resulted in a dataset of 3186 observations. This dataset was then used to test the hypotheses by applying multiple regression.

3.3.1 Multiple regression

Multiple regression is used to model the relationship between the value of some output (the dependent variable) and the parameters that contribute toward that output (the independent variables). It is thus appropriate for testing hypotheses H1 to H5, as there is a single dependent variable (the amount of abuse) and a number of potential contributing factors, split across the hypotheses. More concretely,the dependent variable is *the number of hateful tweets received per day*, and the independent variables (with IV1 mapping to H1 etc.) are as follows:

- **IV1:** domestic club coefficient
- **IV2:** ethnicity (white or other than white)
- **IV3:** match result (coded as lost or did not lose, to avoid ambiguities surround games that went to extra time or penalties)
- **IV4:** penalty outcome (coded as 1 for scored, 0 for did not take, -1 for missed)
- **IV5:** if the player received a red card

In addition, the day of the week was used as a control variable, as previous studies have found that abusive tweets are more likely to be sent on the weekend (Ozalp et al., 2020).

The distribution is modelled as a Poisson process, since the DV is the number of occurrences of an event (an abusive tweet) in a fixed period (24 hours). The variance of the

[10] Domestic club coefficients were correct as of 31st May 2021, approximately two weeks prior to the tournament commencing on 11th June 2021

DV (222.4) is much greater than its mean (1.34) (i.e. the distribution is overdispersed), and so negative binomial regression is used as this removes the restrictive assumption of a Poisson regression that the mean equals the variance. Furthermore, the majority (~84%) of the observations had a value of zero for the dependent variable, making a *zero-inflated negative binomial* (ZINB) regression most suitable (Ozalp et al., 2020).

All data analysis code was written in Python, leveraging the *pandas* library for data manipulation, regression libraries from the *statsmodels* package, and *plotly* for visualisations.

3.3.2 Subsetting and aggregating the data

To support the regression analysis, descriptive data analysis was also carried out. This involved analysing specific matches or players by appropriately subsetting the data, and aggregating relevant variables such as the number of hateful tweets received.

Firstly, the final was analysed separately due to the widely reported online abuse of Saka, Rashford, and Sancho following their penalty shootout misses. Secondly, the number of abusive tweets received by players of different ethnicities were aggregated, for wins and losses separately. For a given match, tweet totals from the matchday and two subsequent days were aggregated, based on a finding from the PFA that online abuse in response to an offline event persisted for around 48 hours after the event (Professional Footballers Association Charity, 2020). The players that missed penalties during their games were omitted from this analysis as a control.

Thirdly, a separate analysis was conducted for players whose teams had been involved in a penalty shootout. As above, tweets were aggregated per player for the two days following a match. As well as looking at the absolute number of abusive tweets received by each player, the proportion of tweets received that were hateful was also analysed.

Finally, H6 was straightforwardly tested by counting the number of hateful tweets received by each player during the entire data collection period.

4. Findings

4.1 The Perspective API identifies hateful tweets with greater accuracy than a search for Hatebase terms, but it has an emoji blindspot

The Perspective API identifies hateful tweets more accurately than the Hatebase approach by all measures, as determined by the manual evaluation of 2,000 tweets according to our definition of hateful language. Figure 2 shows confusion matrices for both approaches. The Perspective approach has a lower false positive rate (0.230 vs. 0.401), lower false negative rate (0.061 vs. 0.146), greater accuracy (i.e. the proportion of predictions that are correct, 0.834 vs. 0.655), greater precision (0.714 vs 0.374), greater recall (0.939 vs 0.854), and a greater F1 score (0.811 vs. 0.520).

The Hatebase approach has a particularly high false positive rate. This is because many of the tweets contain profanities without being hateful, and many of the Hatebase terms are ambiguous. For example, the most identified Hatebase term was “shine”, defined in the Hatebase catalogue as “a black person, originating from their working at shoe shine stands on urban streets or in bus and train station terminals”. However, of the tweets that were manually reviewed the term was mostly used in a supportive manner, for example “@MarcusRashford WE stand with you Marcus, continue to shine”. Given the clear superiority of the Perspective approach, subsequent findings primarily draw on the outputs of this methodology, supported by the Hatebase approach where appropriate.

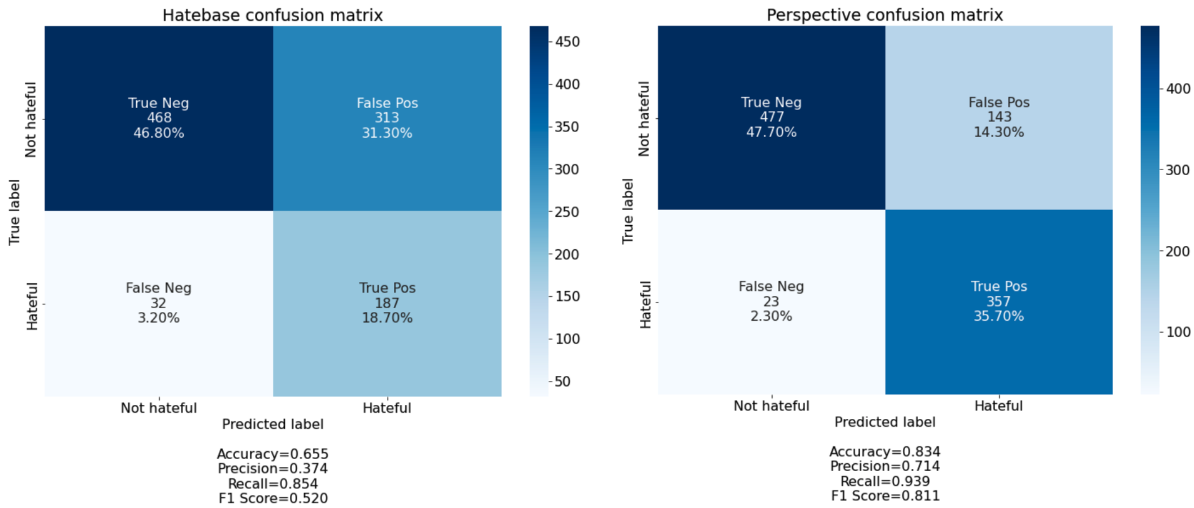

Figure 2: confusion matrices for the Hatebase approach and the Perspective approach. The Perspective approach performs better across the board, having greater accuracy, precision, recall, and F1 score.

Although the Perspective approach is more accurate in general, it does appear to have a blindspot for emoji-based hate. Of the 889 tweets found to contain potentially offensive emojis, a manual review found 84 of them to be hateful. The Perspective method flagged only 11 of these. These 11 tweets are shown in Table 1. They consist of overtly racist text, augmented by emojis. Thus it appears likely that Perspective was able to identify these tweets as offensive primarily by analysing the text alone, whereas it struggled to flag tweets that were less text-based and relied more on the emojis themselves as an expression of hate.

Perspective’s inability to identify emoji-based hate speech supports previous findings by the PFA in 2020, and more recent work by Kirk et al. (2021). Kirk et al. show that models can be trained to better detect such hate speech relatively straightforwardly, by being trained on a larger number of examples of emoji-based hate. There is thus a clear pathway for Google, Twitter, and other organisations developing automated content moderation tools to address this shortcoming.

Tweet text
@AntoGriezmann @Dembouz Hey ! Dembélé🖕 Hey ! Griezmann 🖕 Fucking nigger🦍 Fucking n White pig🐷 You guys are gay guys🥰 You guys are Mother fucker🖕 🤪🤪🤪🤪🤪🤪🤪
@AntoGriezmann @equipedefrance U monkey 🐵🐵🐵!!! Laugh at stupid joke makes u dumb as hell!!! Get ur head out of ur ass dummy!!
@AntoGriezmann Don't pretend to be honest🐒you always call black people chimps in private🐵you cunt
@sterling7 @England DIVING NIGGER 🐵
@sterling7 fuckin cunt , fucking diver .. 🐒🐒🐒🐒🐒
@sterling7 Your good dive nigga💩🙊🙊
@MarcusRashford @Sanchooo10 Niggers 🐒🐒 #England #UEFA #ENGvsITA
@BukayoSaka87 FUCK BLACK LIVES MATTER FUCK YOU TOO BLACK APE🦧🍌🦧🍌 🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒 🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒
@BukayoSaka87 FUCK YOU AND YOUR PENALTY KICK YOU MUST BACK TO THE JUNGLE🐵🐵🐵 🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒 🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒
@BukayoSaka87 Fuck that useless nigger 🐵
Fuck you you fucking black monkeys go back to your disgusting countries and never come back,cost us the hole euros fucking nigger🐒🤬@MarcusRashford @Sanchooo10 and you little prick @BukayoSaka87 #EuroFinal #Euro2021 🤬🐒🐒🐒🐒

Table 1: the 11 hateful tweets containing emoji-based hate flagged by Perspective. There were an additional 73 tweets containing emoji-based hate that the Perspective methodology did not flag.

4.2 Match result, penalty outcome, and ethnicity are all indicative of the amount of abuse received

Predictor	Coefficient	Standard error	p-value
Club coefficient	0.0139	0.001	<0.001
Ethnicity other than White	0.3488	0.152	0.022
Lost match	2.8392	0.395	<0.001
Penalty outcome (-1 = miss, 0 = did not take, 1 = score)	-1.2776	0.398	0.001
Match on Monday	0.6684	46.038	0.988
Match on Tuesday	0.4835	46.038	0.992
Match on Wednesday	0.2682	46.038	0.995
Match on Thursday	-0.3180	46.038	0.994
Match on Friday	-0.9654	46.039	0.983
Match on Saturday	-0.6943	46.039	0.988
Match on Sunday	-0.9686	46.039	0.983

Table 2: Zero-inflated negative binomial regression predicting number of hateful tweets, using data from the Perspective classification methodology.

Table 2 shows the results of the ZINB regression using the more reliable Perspective data. The largest coefficients are for losing a match or missing a penalty, supporting H3 ($p < 0.001$) and H4 ($p = 0.001$). H2 is also supported ($p = 0.022$), as is H1 ($p < 0.001$).

Although the regression supports these hypotheses, it is unlikely that the model is particularly robust. It is built on a relatively small amount of data, which is heavily skewed towards the experiences of the England players given that only English-language tweets were collected and that England progressed to the final of the tournament. Furthermore, the data is heavily skewed towards the events of the final and its aftermath, with 44% of all tweets in the dataset collected on or after 11th July, the day of the final. Additionally, there are only four examples of players missing penalties, all of whom are of ethnicities other than white. As there are no examples of white players missing penalties, it is difficult to accurately model the contributions of ethnicity and penalty outcome to receiving hateful tweets.

Despite the potential shortcomings of the model, additional analysis does provide further support for H2, H3, and H4. Table 3 shows the amount of hateful tweets received by players of different ethnicities, for wins and losses separately. For a given match, tweet totals from the matchday and two subsequent days were aggregated. Only players from Belgium, England, and the Netherlands were included as these three teams both won and lost games during the data collection period. The players who missed penalties, all of whom were of ethnicities other than white, were omitted as a control.

Players received a greater amount of abuse following a loss compared to following a win regardless of the method used to classify a tweet as abusive, or whether comparing the proportion of or absolute number of abusive tweets. This provides strong support for H3. Moreover, this remains mostly true when looking at the two subgroups of white and other than white players separately, with the only exception the proportion of tweets flagged by Perspective for white players, which was 0.14% after both wins and losses.

Furthermore, although just 0.36% of all tweets collected were flagged as hateful by the Perspective classification methodology, the analysis finds that players of ethnicities other than white received a greater amount of abuse than white players. This is particularly pronounced following losses, with the proportion of abuse received by players of ethnicities other than white being nearly five (Perspective) or two (Hatebase) times as large as that of white players. This supports H2. However, one measurement does contradict H2, which is the proportion of tweets flagged by Perspective following a win, which is 0.14% for white players compared to 0.09% for players of ethnicities other than White. This suggests that following a win, the players of ethnicities other than white received a disproportionately high volume of tweets, given they also received a markedly larger number of hateful tweets on average.

	All ethnicities	**White**	**Other than White**
Losses - mean proportion of tweets containing Hatebase slurs for each player	0.91%	0.78%	1.14%
Losses - mean proportion of tweets flagged by Perspective for each player	0.21%	0.14%	0.50%
Losses - mean number of tweets containing Hatebase slurs for each player	13.4	12.2	15.7
Losses - mean number of tweets flagged by Perspective for each player	8.6	7.9	9.8
Wins - mean proportion of tweets containing Hatebase slurs for each player	0.44%	0.31%	0.73%
Wins - mean proportion of tweets flagged by Perspective for each player	0.12%	0.14%	0.09%
Wins - mean number of tweets containing Hatebase slurs for each player	8.6	7.2	11.5
Wins - mean number of tweets flagged by Perspective for each player	6.8	5.9	8.5
Wins or losses - mean proportion of tweets containing Hatebase slurs for each player	0.58%	0.44%	0.85%
Wins or losses - mean proportion of tweets flagged by Perspective for each player	0.15%	0.13%	0.18%
Wins or losses - mean number of tweets containing Hatebase slurs for each player	10.0	8.6	12.8
Wins or losses - mean number of tweets flagged by Perspective for each player	7.3	6.5	8.9

Table 3: proportion and absolute number of tweets identified by the Hatebase and Perspective methods during the two days following a match. Results are presented separately for wins and losses, and for white players and players of ethnicities other than white.

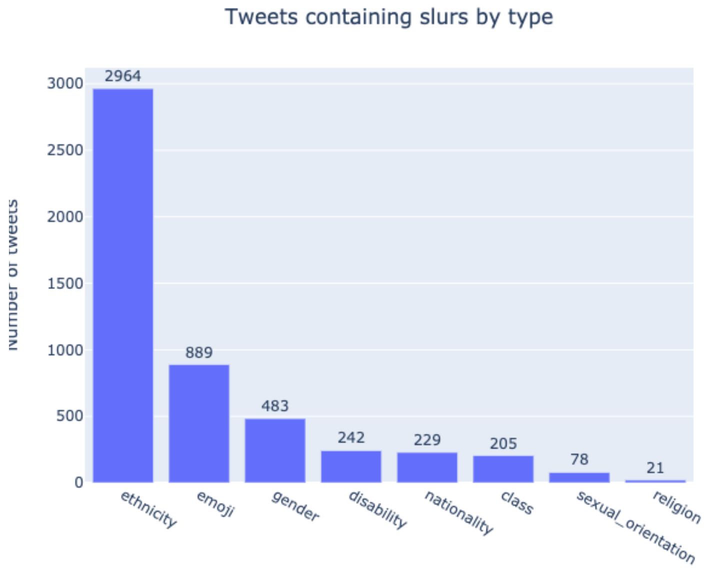

Figure 3: The number of tweets found to contain Hatebase slurs associated with ethnicity, gender, nationality, sexual orientation, class, disability, and religion, as well as those containing potentially offensive emojis.

Figure 4 shows the number of abusive tweets received by players during the two days following their team's involvement in a penalty shootout. There were two such matches in the dataset: France vs Switzerland in the round of 16, and England vs Italy in the final. The shootouts ended in defeat for France and England. Only players who featured in the match (started the match or were substituted on) are included.

These results support H4 in terms of the absolute number of abusive tweets, with the three England players that missed their penalties receiving the largest number of abusive tweets according to both the Hatebase and Perspective methods. Additionally, France forward Kylian Mbappe - the only player to miss a penalty in their shootout defeat to Switzerland - received the fourth largest number of abusive tweets according to Perspective. Although Mbappe is lower in the Hatebase list, this is likely heavily skewed due to only English-language tweets being used; including French-language tweets would paint a fuller picture. The fact that Mbappe appears so high on the Perspective list, and relatively high on the Hatebase list, despite the lack of French-language tweets, provides further evidence in support of H4.

In terms of the proportion of abusive tweets received, things are less conclusive. The four players that missed penalties feature in the top half of the 27 players analysed in terms of the proportion of abusive tweets received for both the Hatebase and Perspective methods. Moreover, according to the Perspective approach, Marcus Rashford received the most abuse of any player in terms of both the absolute number of abusive tweets, and the proportion of abusive tweets. Whilst not as conclusive as the absolute number of tweets, considering the proportion of abusive tweets does appear to lend further support to H4.

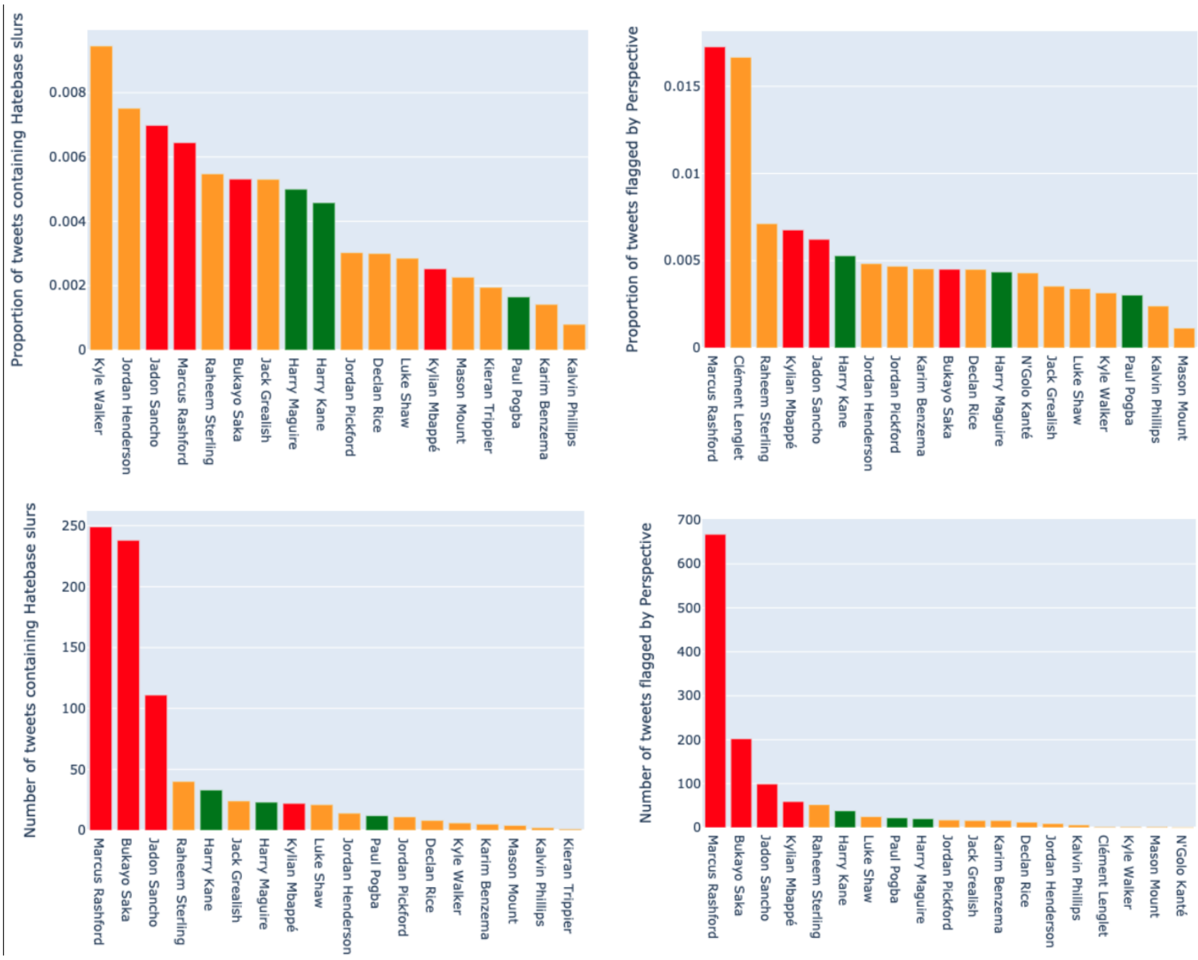

Figure 4: Abusive tweets aimed at players involved in matches featuring penalty shootouts, according to a) the proportion of tweets containing Hatebase slurs; b) the proportion of tweets flagged by Perspective; c) the absolute number of tweets containing Hatebase slurs; d) the absolute number of tweets flagged by Perspective. Red bars indicate the player missed a penalty, green that they scored a penalty, and amber that they did not take a penalty. Note that 8 or 9 players that featured in the matches received no abusive tweets for the Perspective and Hatebase approaches respectively, and are not included on the graphs.

There was insufficient data to test H5. The dataset only contained one example of a player being sent off: Netherlands defender Matthijs de Ligt during a round of sixteen defeat to the Czech Republic. Whilst the data suggests an uptick in tweets containing Hatebase slurs aimed at de Ligt (there were 24 such tweets in the two days following the match, compared to zero the in two days preceding it), the Perspective data does not support this, identifying only one tweet as abusive in the two days following the match. These conflicting results, and the very small sample size, mean there is insufficient evidence to either support or contradict H5.

4.3 The overwhelming majority of hateful tweets are directed at a small number of players

For both the Perspective and Hatebase methodologies, the ten players receiving the largest number of hateful tweets received well in excess of 50% of the total number of hateful tweets sent. Table 4 shows the number of hateful tweets received by these ten players. For the Perspective approach, 3,772 tweets were flagged as offensive, with 3,375 received by the ten most targeted players, representing 89% of all tweets flagged as hateful. For the Hatebase approach, 4,970 tweets contained Hatebase terms and 4,613 of those were targeted at these 10 players, representing 93% of all tweets containing slurs.. These results provide strong support for H6. Indeed, over 50% of the abusive tweets were received by just the three most targeted players.

Name	Number of tweets containing Hatebase terms
Marcus Rashford	1177
Bukayo Saka	845
Harry Kane	498
Jadon Sancho	481
Raheem Sterling	419
Jack Grealish	407
Romelu Lukaku	234
Tyrone Mings	224
Harry Maguire	173
Antoinne Griezmann	155

Name	Number of tweets flagged by Perspective
Marcus Rashford	1182
Bukayo Saka	444
Raheem Sterling	419
Harry Kane	412
Antoinne Griezmann	247
Jadon Sancho	247
Jack Grealish	127
Kylian Mbappe	125
Tyrone Mings	95
Jordan Henderson	77

Table 4: the ten players that received the greatest number of potentially abusive tweets during the entire data collection period for the Hatebase and Perspective classification methodologies.

4.4 The final was a major flashpoint for abuse

The final of the tournament between England and Italy on 11th July proved a flashpoint for abuse. The game was decided by a penalty shootout in which England players Marcus Rashford, Jadon Sancho, and Bukayo Saka - all players of ethnicities other than White - missed penalties, as Italy won the competition. This triggered a wave of hateful tweets directly targeting these three players, including numerous examples of extremely overt racism. Table 5 shows a sample of such tweets, which encourage suicide, include references to slavery, and employ monkey and banana emojis to express racial hate.

Time	Tweet
21:58	"@MarcusRashford @saka @Sanchooo10 The civil rights for black people have been revoked in england now?"
22:00	"@MarcusRashford YOU FUCKING SLIMY SUBHUMAN BANANA EATING LITTLE BITCH. I hope you deactivate your account and then kill yourself from the abuse, I genuinely do."
22:01	"@MarcusRashford @ChrisEriksen8 @DBUfodbold COME BACK TO JUNGLE MOTHER FUCKER DONKEY 🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🐒🍌🍌🍌🐒🐒🐒"
22:06	"@MarcusRashford how did you miss that you fuckinh black bastard"
22:13	"Bring back slavery cah these niggers not working hard enough @Sanchooo10 @BukayoSaka87 @MarcusRashford all need to get whipped"
22:14	"Saka you dirty nigga wtf...Rashford as for you you need to kys [kill yourself] you dirty nigga slave no words boys go back to your own country this isn't even your home.. @MarcusRashford @BukayoSaka87"
23:15	"@BukayoSaka87 This's what get for letting these subhuman wogs play for your national team. England is fucking doomed."

Table 5: examples of overtly racist tweets directed at Bukayo Saka, Marcus Rashford, and Jadon Sancho in the aftermath of England's penalty shootout defeat to Italy in the final of the European Championships

Although this study did not investigate content moderation or enforcement of Twitter's hateful conduct policy,[11] it is worth noting that all tweets listed in Table 5 had been removed from Twitter when checked on 22nd August 2021. Two of the accounts that posted the tweets had

[11] See https://help.twitter.com/en/rules-and-policies/hateful-conduct-policy [Accessed 23rd August 2021]

been suspended, one temporarily restricted, but four remained active. Of those four accounts, one also sent an overtly racist tweet to Raheem Sterling during the Champions League final on May 29th 2021, which was still up on Twitter on 22nd August. Additionally, another of these accounts had recently posted tweets encouraging self-harm. It appears that Twitter's content moderation process may have successfully deleted the most overtly racist tweets following the final of the European Championships, but at least some of the accounts that posted such abuse continue to actively post hateful or harmful content on Twitter, in apparent violation of its terms of service. More in-depth research is needed to clarify this picture.

The final kicked off at 19:00 UTC, and ended with Saka's decisive penalty miss at approximately 21:54 UTC. The conclusion of the match led to a large spike in tweets, with both the number of tweets and the number of abusive tweets reaching their maximum frequency of any point during the data collection period. Table 6 shows the number of hateful tweets received by England players in the 5 days following the final, as flagged by Perspective. There were 1,739 hateful messages directed at Saka, Rashford, and Sancho, accounting for 77% of all the hateful messages identified during this period. The three players clearly received a disproportionate amount of abuse on social media in the aftermath of the final.

In order to understand the type of abuse aimed at players following the final, all tweets flagged by Perspective were searched for the list of Hatebase terms. As each Hatebase term is associated with different types of abuse, this enabled an association between tweets flagged by Perspective and the type of abuse they contain to be established. Results for this are shown in Figure 5, and indicate that tweets containing ethnic slurs were most prominent. This supports anecdotal evidence of Saka, Rashford, and Sancho being targeted with a significant number of racist tweets.

Name	Number of tweets flagged by Perspective
Marcus Rashford	1139
Bukayo Saka	400
Jadon Sancho	200
Harry Kane	105
Tyrone Mings	91
Raheem Sterling	80
Jack Grealish	60
Harry Maguire	39
Luke Shaw	28
Jordan Pickford	24

Table 6: the number of hateful tweets received by England players from 9:54pm on 11th July (the end of the final) to midnight on 17th July.

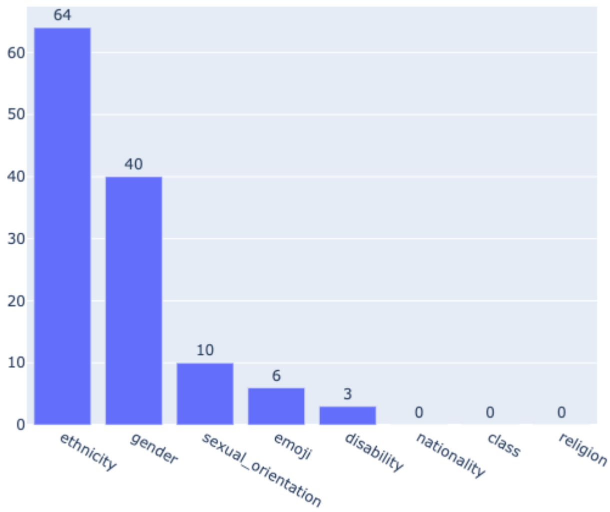

Figure 5: number of tweets flagged by Perspective that contain Hatebase terms by the type of hate they are associated with.

Spikes in tweets in the days following the final came in response to tweets posted by Rashford, Sancho, and Saka. These tweets also provoked a greater number of hateful tweets, notably in Rashford's case. Figure 6 shows the frequency of tweets during this period. This finding - that tweeting in response to abuse provokes additional abuse -

resonates with previous findings from the PFA and ADL on the experiences of Raheem Sterling, Wilfried Zaha, Adebayo Akinfenwa, and Jonathan Weisman.

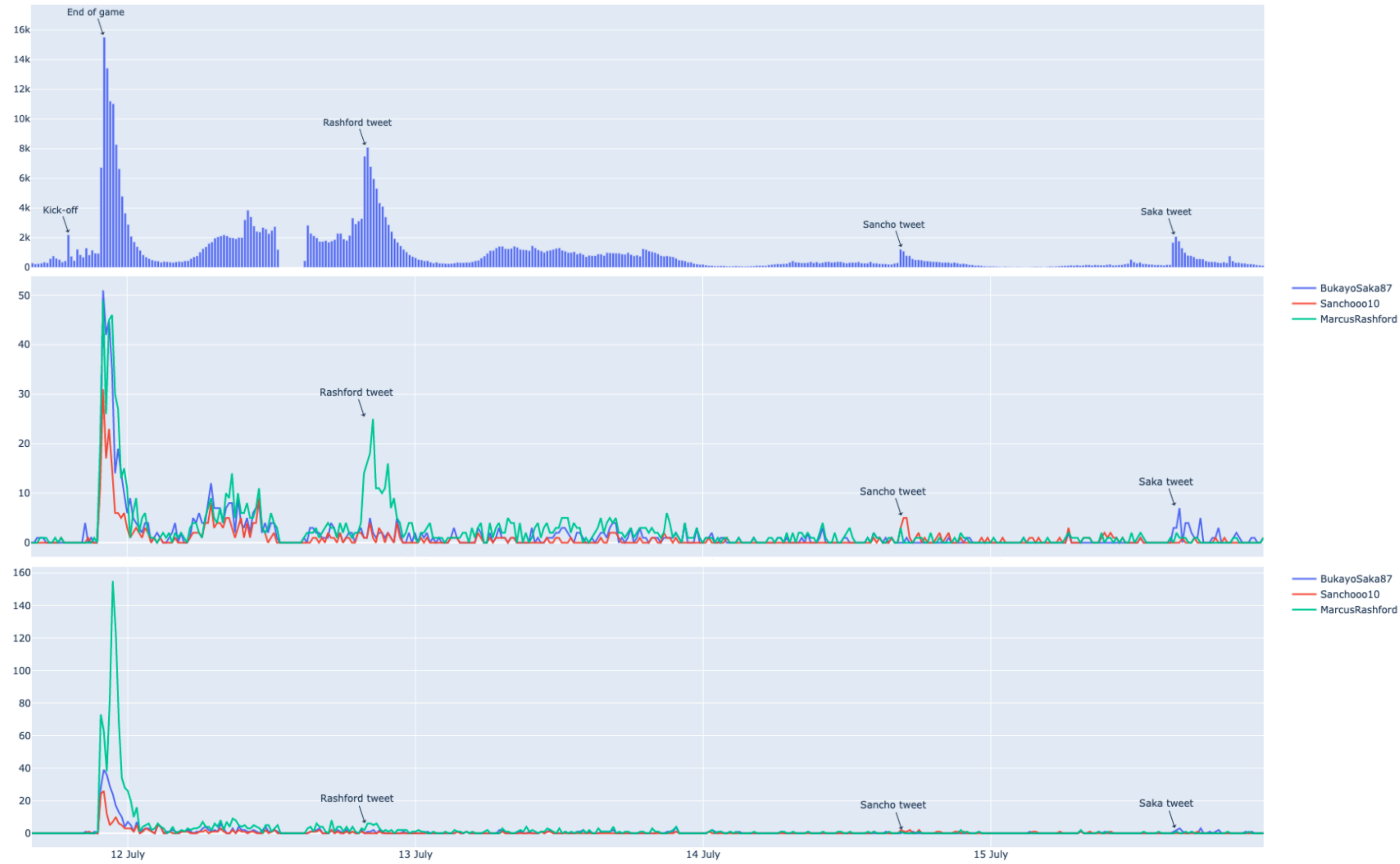

Figure 6: number of tweets during the final and its aftermath, aggregated in 15 minute bins. a) total number of tweets received by all England players; b) number of tweets containing Hatebase slurs for Rashford, Sancho, and Saka; c) number of tweets flagged by Perspective for Rashford, Sancho, and Saka. Note there is missing data on 12th July between 12:37pm and 2:55pm UTC.

5. Conclusion

5.1 Implications of the research

The analysis shows that England's Marcus Rashford, Bukayo Saka, and Raheem Sterling received the largest number of hateful tweets during the 2020 European Championship. This answers RQ1, but with the caveat that including only English-language tweets likely skewed results towards English players. The study also provides evidence that the amount of hateful tweets directed at footballers during the tournament was heavily influenced by offline events. Losing a match or missing a penalty were strongly associated with an increase in hateful messages, and these two factors together provide an answer to RQ3. This finding is also consistent with previous anecdotal reports of abuse being aimed at players because of their on-field performances, as discussed in Section 2.4. Moreover, tweets by Bukayo Saka, Marcus Rashford, and Jadon Sancho in the days following their penalty misses in the final provoked further waves of hateful messages, in line with findings from previous research into racist abuse of footballers and antisemitic abuse of journalists on social media.

The analysis provides an answer to RQ2, showing that ethnicity does influence the volume of hateful messages received, with players of ethnicities other than white receiving a greater number of hateful tweets. Moreover, there is evidence that a significant proportion of this abuse was racist in nature, containing slurs relating to ethnicity. This finding is perhaps expected, given the numerous media reports of the abuse received by Bukayo Saka, Jadon Sancho, and Marcus Rashford following their penalty misses in the final. Importantly however, this finding holds even when these players are omitted from the analysis (along with Kylian Mbappe, the player who missed France's decisive penalty). There is thus compelling evidence that throughout the tournament white players were less likely to be targeted with hateful tweets than players of other ethnicities. Drawing again on Bonilla-Silva's dramaturgical analogy, it is evident that Twitter has provided a mechanism for racist expressions of hate to move *frontstage*.

Whilst there have been several studies of online hate in domestic football, particularly in England, this study appears to be the first to analyse the issue in-depth during international competition. It provides empirical evidence that the issue of online hate towards footballers is not restricted to the domestic game. In addition to the findings of this study being noteworthy, the author hopes the dataset itself can be useful for further research into the manifestation of football-related online hate speech.

The study also provides an answer to RQ4, highlighting the strength of machine learning-based methods for detecting hateful speech over the cruder approach of searching for hateful terms. The latter is particularly prone to false positives, meaning studies adopting this approach may be at serious risk of overcounting the number of hateful tweets, and thus overstating the magnitude of the problem. Analysis by the Guardian during the group stages of the tournament adopted such an approach, but importantly employed a subsequent manual review step of all tweets containing hateful terms to remove these false positives (Barr et al., 2021). Whilst this second step will have improved the precision of the classification, it will have had no effect on the recall, which is likely to have been worse than what could have been achieved by leveraging a machine learning-based tool like Perspective. Although further work is needed to expand Perspective to more languages, and to resolve some of its blindspots - such as the poor performance on emoji-based hate speech - the fact that Perspective is free to access, straightforward to use, and generally more accurate suggests that future studies of online hate may be well-advised to adopt the Perspective methodology used in this study, especially over performing a search for hateful terms.

5.2 Limitations and future work

Unfortunately there was insufficient data to test H5. In order to test this hypothesis, a longer study is needed covering a large number of games so that enough red cards are issued for an analysis on a red card’s influence on abusive tweets to have statistical power.

Future work should more thoroughly assess the accuracy of the methods used to identify abusive tweets. In this study, the thresholds for classifying tweets as abusive were chosen so as to provide a focus on the most unambiguous hateful messages, but the choice of threshold was somewhat arbitrary. Future work should experiment with different thresholds for both the Perspective and Hatebase approaches, in order to better understand the tradeoffs involved. Moreover, to overcome the Perspective model's apparent blindspot to emoji-based hate, a model that has been trained on emoji-based hate speech, such as that recently developed by Kirk et al. (2021), could be employed.

Furthermore, one limitation of both methods used to identify abusive tweets is that they do not have the context-awareness to understand whether the abuse is actually being directed at the account of the footballer tagged in the tweet. A noteworthy example of this followed a tweet by a prominent political commentator that tagged Marcus Rashford and directed him to "stick to penalties not politics". This triggered a wave of replies which were correctly identified by our methods as hateful. However, many of them were clearly directed at the commentator, but because both they and Rashford were tagged, these tweets contributed towards the count of hateful tweets aimed at Rashford. One possible method to avoid this would be to only consider tweets where a single account is tagged. This would likely reduce the number of false positives, but at the cost of increasing the number of false negatives. Further work is needed to investigate methods for accurately determining the target of an offensive tweet.

Future work could also address some of the limitations in the data collection process. Firstly, tweets from languages other than English could be included, which would be particularly useful for identifying hate speech aimed at players from non-English-speaking nations. An added complication is that this would require methods for classifying hate speech that support other languages. Some of the attributes returned by the Perspective API do support languages including Spanish, French, German, Portuguese, Italian, and Russian. Future research could leverage the Perspective API to analyse tweets in these languages.

Additionally, the data collection could be expanded from just tracking the Twitter handles of the players to also track tweets that mention their names, but not their handles. This would significantly increase the number of tweets collected, but would provide a fuller understanding of the online conversation surrounding the players. Furthermore, it could be informative to include tweets about the coaches of the teams - the Guardian's analysis found that England head coach Gareth Southgate received more abuse than any of his players during the group stages of the tournament (Barr et al., 2021). Retweets could also be included (these were excluded from the data collection in order to minimise the likelihood of hitting Twitter's cap on the number of tweets that can be collected), which could facilitate analysis to understand how hateful tweets proliferate across the platform.

A final area for possible research would be a focus on homomphobic abuse on social media. During the tournament, France's Antoinne Griezmann, England's Jordan Henderson, and Germany's Manuel Neuer spoke out in support of LGBTQ+ rights, with Neuer sporting a rainbow captain's armband in solidarity with the LGBTQ+ movement. This support provoked particularly strong reactions as both France and Germany played Hungary in the group stages at a time where the Hungarian government were implementing controversial anti-LGBTQ+ laws. There are examples in the data of the three players receiving homophobic abuse because of their stance, which warrants more detailed investigation.

5.3 Closing remarks

The above limitations highlight the challenges involved in conducting effective social science research on social media platform data. Despite these shortcomings, the research provides clear evidence of footballers receiving hateful speech on Twitter during the European Championships, much of which was racist in nature. Whilst it appears that Twitter's content moderation process was effective in removing the most overtly hateful tweets after the fact, methods for proactively preventing the proliferation of such messages could greatly reduce harm.

Online hate and discrimination affects many people each day, some of whom will be in much more vulnerable positions than the footballers analysed in this dissertation. But we can use football as a catalyst for change. It is the world’s most popular sport, and we should leverage its popularity to raise awareness and bring attention to all forms of online hate. This can encourage greater action to tackle these challenges, which will benefit all in society. It is the author’s hope that this dissertation can contribute in small part to these efforts.

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Appendix A - Twitter accounts for data collection

The tables below list the 118 player accounts for which tweet data was collected.

Player	Country	Domestic team	Twitter handle
Thibaut Courtois	Belgium	Real Madrid, Spain	thibautcourtois
Toby Alderweireld	Belgium	Tottenham Hotspur, England	AlderweireldTob
Thomas Vermaelen	Belgium	Vissel Kobe, Japan	thomasvermaelen
Jan Vertonghen	Belgium	Benfica, Portugal	JanVertonghen
Axel Witsel	Belgium	Borussia Dortmund, Germany	axelwitsel28
Kevin De Bruyne	Belgium	Manchester City, England	DeBruyneKev
Romelu Lukaku	Belgium	Internazionale, Italy	RomeluLukaku9
Eden Hazard	Belgium	Real Madrid, Spain	hazardeden10
Yannick Carrasco	Belgium	Atlético Madrid, Spain	CarrascoY21
Simon Mignolet	Belgium	Club Brugge, Belgium	SMignolet
Dries Mertens	Belgium	Napoli, Italy	dries_mertens14
Thomas Meunier	Belgium	Borussia Dortmund, Germany	ThomMills
Thorgan Hazard	Belgium	Borussia Dortmund, Germany	HazardThorgan8
Hans Vanaken	Belgium	Club Brugge, Belgium	VanakenHans
Jason Denayer	Belgium	Lyon, France	Jasondenayer
Christian Benteke	Belgium	Crystal Palace, England	chrisbenteke
Nacer Chadli	Belgium	İstanbul Başakşehir, Turkey	NChadli
Michy Batshuayi	Belgium	Crystal Palace, England	mbatshuayi
Leandro Trossard	Belgium	Brighton & Hove Albion, England	LTrossard
Jérémy Doku	Belgium	Rennes, France	JeremyDoku
Dennis Praet	Belgium	Leicester City, England	dennispraet
Joël Veltman	Netherlands	Brighton & Hove Albion, England	joel_veltman
Matthijs de Ligt	Netherlands	Juventus, Italy	mdeligt_04
Nathan Aké	Netherlands	Manchester City, England	NathanAke
Stefan de Vrij	Netherlands	Internazionale, Italy	Stefandevrij
Georginio Wijnaldum	Netherlands	Liverpool, England	GWijnaldum
Luuk de Jong	Netherlands	Sevilla, Spain	LuukdeJong9
Memphis Depay	Netherlands	Lyon, France	Memphis
Quincy Promes	Netherlands	Spartak Moscow, Russia	QPromes
Patrick van Aanholt	Netherlands	Crystal Palace, England	pvanaanholt
Tim Krul	Netherlands	Norwich City, England	TimKrul
Davy Klaassen	Netherlands	Ajax, Netherlands	DavyKlaassen
Marten de Roon	Netherlands	Atalanta, Italy	Dirono
Ryan Gravenberch	Netherlands	Ajax, Netherlands	RGravenberch
Daley Blind	Netherlands	Ajax, Netherlands	BlindDaley

Frenkie de Jong	Netherlands	Barcelona, Spain	DeJongFrenkie21
Denzel Dumfries	Netherlands	PSV Eindhoven, Netherlands	DenzelJMD2
Jordan Pickford	England	Everton, England	JPickford1
Kyle Walker	England	Manchester City, England	kylewalker2
Luke Shaw	England	Manchester United, England	LukeShaw23
Declan Rice	England	West Ham United, England	_DeclanRice
Harry Maguire	England	Manchester United, England	HarryMaguire93
Jack Grealish	England	Aston Villa, England	JackGrealish
Jordan Henderson	England	Liverpool, England	JHenderson
Harry Kane	England	Tottenham Hotspur, England	HKane
Raheem Sterling	England	Manchester City, England	sterling7
Marcus Rashford	England	Manchester United, England	MarcusRashford
Kieran Trippier	England	Atlético Madrid, Spain	trippier2
Dean Henderson	England	Manchester United, England	deanhenderson
Kalvin Phillips	England	Leeds United, England	Kalvinphillips
Tyrone Mings	England	Aston Villa, England	OfficialTM_3
Jadon Sancho	England	Borussia Dortmund, Germany	Sanchooo10
Dominic Calvert-Lewin	England	Everton, England	CalvertLewin14
Mason Mount	England	Chelsea, England	masonmount_10
Phil Foden	England	Manchester City, England	PhilFoden
Ben Chilwell	England	Chelsea, England	BenChilwell
Ben White	England	Brighton & Hove Albion, England	ben6white
Sam Johnstone	England	West Bromwich Albion, England	samjohnstone50
Reece James	England	Chelsea, England	reecejames_24
Bukayo Saka	England	Arsenal, England	BukayoSaka87
Jude Bellingham	England	Borussia Dortmund, Germany	BellinghamJude
David Marshall	Scotland	Derby County, England	MarshallDavid23
Stephen O'Donnell	Scotland	Motherwell, Scotland	sodonnell15
Andrew Robertson	Scotland	Liverpool, England	andrewrobertso5
Scott McTominay	Scotland	Manchester United, England	mctominay10
Grant Hanley	Scotland	Norwich City, England	granthanley5
Kieran Tierney	Scotland	Arsenal, England	kierantierney1
John McGinn	Scotland	Aston Villa, England	jmcginn7
Callum McGregor	Scotland	Celtic, Scotland	Callummcgregor8
Lyndon Dykes	Scotland	Queens Park Rangers, England	Lyndon_Dykes
Ché Adams	Scotland	Southampton, England	CheAdams_
Craig Gordon	Scotland	Heart of Midlothian, Scotland	CraigGordon01
Declan Gallagher	Scotland	Motherwell, Scotland	declang31

Liam Cooper	Scotland	Leeds United, England	LiamCooper__
David Turnbull	Scotland	Celtic, Scotland	10DavidTurnbull
Kevin Nisbet	Scotland	Hibernian, Scotland	kevinnisbet16
Nathan Patterson	Scotland	Rangers, Scotland	np4tterson
Billy Gilmour	Scotland	Chelsea, England	billygilmourrr
Jack Hendry	Scotland	Oostende, Belgium	Jack_Hendry2
Scott McKenna	Scotland	Nottingham Forest, England	Scottmckenna3
Benjamin Pavard	France	Bayern Munich, Germany	BenPavard28
Presnel Kimpembe	France	Paris Saint-Germain, France	kimpembe_3
Raphaël Varane	France	Real Madrid, Spain	raphaelvarane
Clément Lenglet	France	Barcelona, Spain	clement_lenglet
Paul Pogba	France	Manchester United, England	paulpogba
Antoine Griezmann	France	Barcelona, Spain	AntoGriezmann
Olivier Giroud	France	Chelsea, England	_OlivierGiroud_
Kylian Mbappé	France	Paris Saint-Germain, France	KMbappe
Corentin Tolisso	France	Bayern Munich, Germany	CorentinTolisso
N'Golo Kanté	France	Chelsea, England	nglkante
Kurt Zouma	France	Chelsea, England	KurtZouma
Steve Mandanda	France	Marseille, France	SteveMandanda
Moussa Sissoko	France	Tottenham Hotspur, England	MoussaSissoko
Lucas Digne	France	Everton, England	LucasDigne
Karim Benzema	France	Real Madrid, Spain	Benzema
Lucas Hernandez	France	Bayern Munich, Germany	LucasHernandez
Wissam Ben Yedder	France	Monaco, France	WissBenYedder
Mike Maignan	France	Lille, France	mmseize
Léo Dubois	France	Lyon, France	leodubois15
Jules Koundé	France	Sevilla, Spain	jkeey4
Marcus Thuram	France	Borussia Mönchengladbach, Germany	MarcusThuram
Manuel Neuer	Germany	Bayern Munich, Germany	Manuel_Neuer
Antonio Rüdiger	Germany	Chelsea, England	ToniRuediger
Matthias Ginter	Germany	Borussia Mönchengladbach, Germany	MatzeGinter
Mats Hummels	Germany	Borussia Dortmund, Germany	matshummels
Kai Havertz	Germany	Chelsea, England	kaihavertz29
Toni Kroos	Germany	Real Madrid, Spain	ToniKroos
Kevin Volland	Germany	Monaco, France	KeVolland
Serge Gnabry	Germany	Bayern Munich, Germany	SergeGnabry
Bernd Leno	Germany	Arsenal, England	Bernd_Leno
Jamal Musiala	Germany	Bayern Munich, Germany	JamalMusiala

Lukas Klostermann	Germany	RB Leipzig, Germany	lukaskl96
Leon Goretzka	Germany	Bayern Munich, Germany	leongoretzka_
Leroy Sané	Germany	Bayern Munich, Germany	leroy_sane
İlkay Gündoğan	Germany	Manchester City, England	IlkayGuendogan
Emre Can	Germany	Borussia Dortmund, Germany	emrecan_
Robin Koch	Germany	Leeds United, England	RobinKoch25
Thomas Müller	Germany	Bayern Munich, Germany	esmuellert_

Appendix B - Fixtures covered in analysis

* indicates team won by penalty shootout

Date	Kick-off time	Stage	Team A	Team B	Result
18/06/2021	20:00	Group	England	Scotland	0-0
19/06/2021	14:00	Group	Hungary	France	1-1
19/06/2021	17:00	Group	Portugal	Germany	2-4
21/06/2021	17:00	Group	North Macedonia	Netherlands	0-3
21/06/2021	20:00	Group	Finland	Belgium	0-2
22/06/2021	20:00	Group	Croatia	Scotland	3-1
22/06/2021	20:00	Group	Czech Republic	England	0-1
23/06/2021	20:00	Group	Germany	Hungary	2-2
23/06/2021	20:00	Group	Portugal	France	2-2
27/06/2021	17:00	Round of 16	Netherlands	Czech Republic	0-2
27/06/2021	20:00	Round of 16	Belgium	Portugal	1-0
28/06/2021	20:00	Round of 16	France	Switzerland	3-3*
29/06/2021	17:00	Round of 16	England	Germany	2-0
02/07/2021	20:00	Quarter final	Belgium	Italy	1-2
03/07/2021	20:00	Quarter final	Ukraine	England	0-4
07/07/2021	20:00	Semi final	England	Denmark	2-1
11/07/2021	20:00	Final	Italy	England	*1-1