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Video assistant referee on Twitter: a text-mining-based analysis of fan sentiment
Árbitro asistente de vídeo en Twitter: un análisis del sentimiento de los fans basado en la minería de textos

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Resumen. El objetivo de la investigación era conocer la opinión de los usuarios de Twitter sobre el Video Assistant Referee, conocido por el acrónimo VAR, durante su implantación en la Premier League, a través de las palabras, emojis y temas más relacionados con los términos de búsqueda. Mediante un algoritmo, se realizó una búsqueda sistemática de una serie de palabras utilizadas en la red social Twitter. El resultado de esta búsqueda se procesó con la intención de obtener resultados cuantitativos en términos de frecuencia de palabras buscadas, términos y emojis que las acompañan, así como temas emergentes. Los resultados mostraron que, entre los bigramas, "premier league" era el más repetido. Entre los trigramas, la asociación entre las palabras "var ruin football" y "var kill football". Los principales temas encontrados contenían las palabras "ruin", "football", "fuck" y "kill". De los emojis más utilizados, sólo dos tenían connotaciones positivas. En conclusión, se observó una tendencia de opinión negativa sobre el VAR.
Palabras clave: var, football, fútbol, fans, Twitter, análisis de datos.

Abstract. The objective of the research was to know the opinion of Twitter users about the Video Assistant Referee, known by the acronym VAR, during its implantation in the Premier League, through the words, emojis and topics most related to the search terms. Using an algorithm, a systematic search was carried out during a given period of time for a series of words used in the Twitter social network. The result of this search was processed to obtain quantitative results in terms of the frequency of the searched words, terms and emojis that accompanied them as well as emerging themes. The results showed that among the bigrams, "premier league" was the most repeated. Among the trigrams, the association between the words "var ruin football" and "var kill football" stands out. The main themes found contained the words "ruin", "football", "fuck" and "kill". Of the most used emojis, only two had positive connotations. In conclusion, a trend of negative opinions about VAR was observed.
Keywords: var, football, soccer, fans, Twitter, data analysis.

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Introduction

Sports referees have an important responsibility to manage sporting competitions at the highest level of play fairly and accurately (Mascarenhas, Collins, & Mortimer, 2005). For this reason, they play a pivotal role, and their importance is highlighted by the contribution that their decisions, right or wrong, can make to the final outcome of a sporting contest (Larkin, Berry, Dawson, & Lay, 2011). Their performance can influence the success of athletes and teams during professional competitions that have an enormous social and economic impact (Aza Conejo, Banos-Pino, Canal Dominguez, & Rodriguez Guerrero, 2007; Barajas & Urrutia, 2007; Brymer, Rodenberg, Zheng, & Holcomb, 2021).

In the case of football, referees are the impartial judges responsible for exercising authority, applying the rules, and interpreting the rules on the field of play. However, they can exercise discretionary powers that can be substantial and affected by subjectivity, such as extra time, the awarding of penalties, the awarding of yellow or red cards, the decision on free kicks, or offside infringements (Sutter & Kocher, 2004). To reduce the subjectivity component and improve decision-making by making it more accurate, technological tools have been introduced in football, which have been used in other sports before (Tingle & Armenteros, 2019). One of these tools is the Video Assistant Referee (VAR). After a testing phase that started in 2012, VAR technology was implemented in FIFA Regulations in 2018 (Fédération Internationale de Football Association, 2019). Since its introduction, VAR has monitored the main referee's decisions and the application of the rules, with the aim of increasing fairness and assisting during decision-making in the following four situations: goals, penalties, direct red card situations, and administrative incidents. The procedure is as follows: during a match, the assistants in a booth constantly watch video images and, if they consider it necessary, inform the main referee of the existence of a doubtful situation. The main referee, if necessary, can accept the information provided by the VAR, or he can review the images himself thanks to a monitor installed for this purpose on one side of the field of play. The final decision on the play in question rests with the head referee alone. In short, VAR is a technological innovation at the service of controlling the referees' decisions, warning of possible errors, and allowing the review of actions that involve doubts, combining human appreciation and the technological component (in this case, a video and audio system) (Sanchez & Garcia, 2019). The implementation of such a novelty, especially taking into account that football has been a sport very little given to rule variations throughout its history (Garland, Malcolm, & Rowe, 2013), has generated a diversity of opinions among fans around the world (Coombs & Osborne, 2022; Fişne, Bardakçi, & Hasaan, 2021; Scanlon, Griggs, & McGillick, 2022; Winand, Schneiders, Merten, & Marlier, 2021).

Today, and since the emergence of Internet applications where users can generate and share content, the approach and the way in which people obtain and share information have changed radically (van Dijck & Poell, 2013). In particular, social networks have become major communication channels that have given voice to all social actors: individuals, companies, and institutions (Dawley, 2009; Yao, Li, Song, & Crabbe, 2021). The scientific community has studied these new channels, particularly the microblogging network Twitter. As a global social network, it allows researchers to predict and monitor people's behaviors and even their attitudes or feelings (Alharbi & de Doncker, 2019); proving to be an instrument of communication and social representation of undoubted importance for the academic world. The structural dynamics of this network allow for obtaining relevant information through big data analysis techniques related to the data flowing through microblogging in synchronic and diachronic analysis of the activity happening on this network (Kearney, 2019; Marres & Weltevrede, 2013).

Through these tools, people's opinions and feelings about football have been investigated directly and by capturing information during the viewing of the matches themselves, using novel big data analysis techniques (Wunderlich & Memmert, 2022). However, so far, due to its recent incorporation into the sport, the opinions and feelings generated by the VAR after its admission to the sport of football have not been analyzed using novel big data techniques. Therefore, the present study aims to discover the opinion of Twitter users about the VAR, through the words, emojis, and topics that are most related to the search concepts.

Materials and Methods

Blok and Pedersen (2014) discussed how different methodologies, such as quantitative and qualitative, can be complementary and essential for mutual understanding. The methodology employed in this study aims to address the need identified by Tinati et al. (2014). In their work, they explained the importance of adding meaning to big data obtained from Twitter by combining methodologies that leverage the technical capabilities of computer science and in-depth qualitative research methods. In this study, we seek to approach the macrostructure of the data through quantitative algorithms, while qualitative content analysis allows us to delve into the meaning of tweets at the micro level. Thus, the qualitative approach to the data involves interpretative steps, maintaining the advantages of quantitative analysis (Mayring, 2015).

2.1. Data Retrieval and Preprocessing

A script was written in the MATLAB environment (R2022b, Mathworks Inc., Natick, MA, USA) to perform queries through the Twitter search API and build our database. Since the search was conducted in English, it was deemed appropriate to focus on the English league or Premier League, as it is one of the most important English-speaking soccer leagues and where the VAR has been implemented since 2019. However, the possibility of finding tweets from other English-speaking regions was not ruled out. The search function was as follows: FI = '(VAR OR #VAR) (premier OR "premier league" OR football OR soccer OR referee)'. Note that the "AND" logic is specified in the API with a space between clauses. Daily systematic searches were performed using these terms, downloading all tweets posted on the topic using the "recent," "popular," and "mixed" search options.

The data were stored in JSON format, with files containing information about each found tweet and the user who had produced or retweeted it. These files contained over 150 attributes, of which we only used 11 for this work. The first formal search for our study was performed on January 1, and the last one on May 10. A total of 1,717,866 tweets were retrieved. Finally, after removing duplicates, replies, and retweets, a total of 54,677 tweets were obtained.

Figures 1 and 2 present the geographical areas where part of the collected tweets is located. Specifically, the first shows tweets worldwide, and the second in the United Kingdom.

To prepare the text of the tweets for further analysis, standard recommendations used in similar studies were followed (Jianqiang & Xiaolin, 2017). The documents were reduced to tokens, and different actions were performed in the following order:

1. All hyperlinks ("http://url"), hashtags ("#hashtag"), emojis, and username links ("@username") appearing in the tweets were removed.

2. Punctuation marks and special characters were removed.

3. Words were converted to lowercase.

4. Words that could add noise to the text and did not add content to the tweets (e.g., "a," "and") were removed. However, not all empty words in the list of keywords that the MATLAB text analysis toolbox has by default were discarded, as some have value and meaning for sentiment analysis.

5. The words were normalized by a lemmatization process, where morphological analysis was performed to reduce them to their roots, using a predefined dictionary. To improve the process, part-of-speech details were added to indicate whether the word was a noun, verb, adjective, etc.

6. Words with less than 2 or more than 20 characters, and whose frequency in the document corpus was less than 2, were also removed.

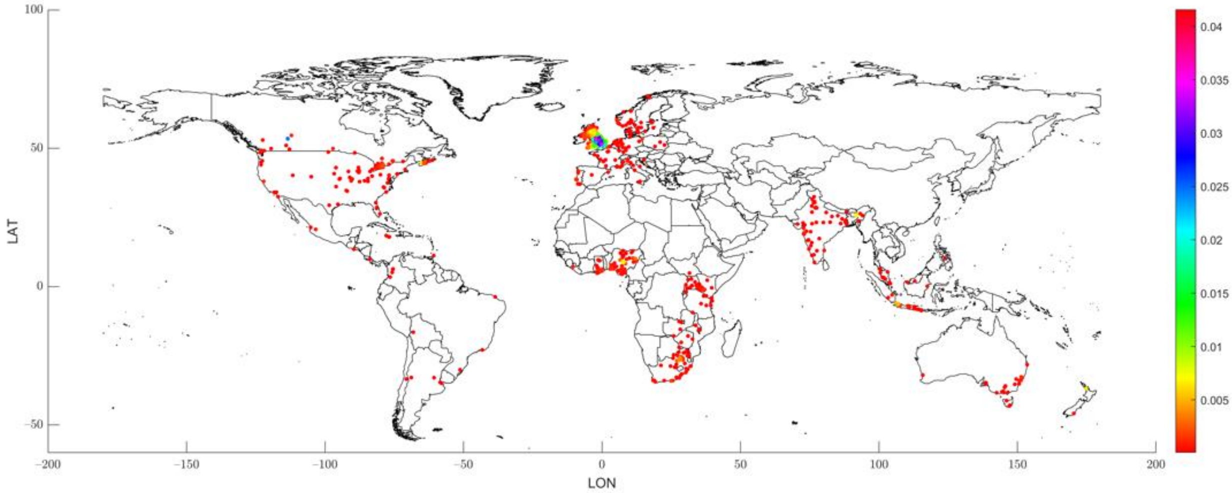

Figure 1. Mundial geolocation of tweets published. The three-dimensional color bars show the density of tweets (kernel density). Larger size indicates a higher density of tweets in the area. Only those tweets that were geo-tagged are shown (n = 9682).

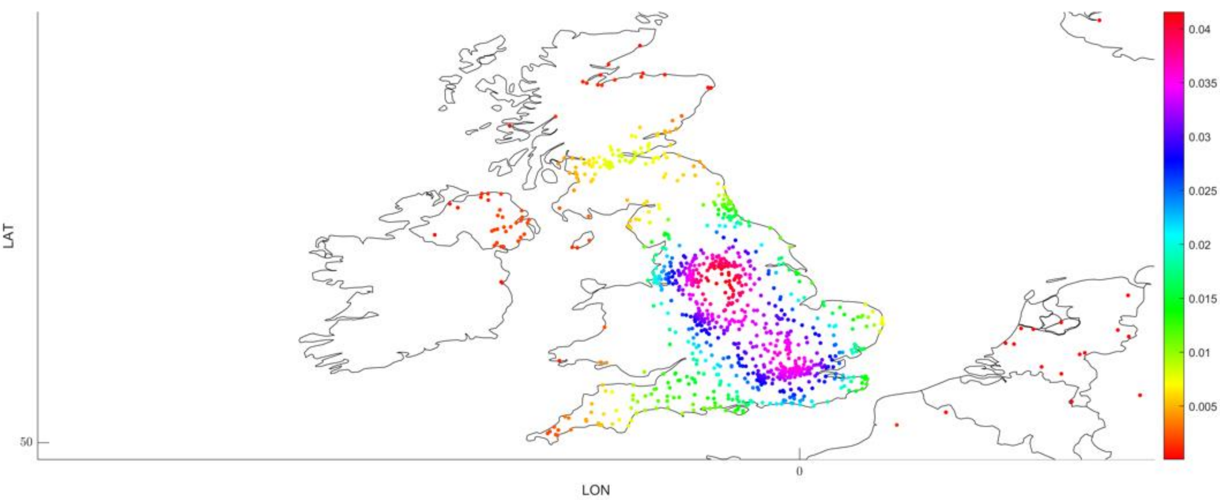

Figure 2. United Kingdom geolocation of tweets published. The three-dimensional color bars show the density of tweets (kernel density). Larger size indicates a higher density of tweets in the area.

The resulting tokens were used to form word sets, unigrams, bigrams, and trigrams. An n-gram is a substring of n elements of a given sequence of the original documents; raw data and associated fields were also stored for quantitative analysis to analyze some of the attributes containing text, e.g., the most frequently mentioned entities and users, although most of these attributes were not processed in any way.

With the intention of establishing the growth and decline of the most frequently cited words over the data collection period, these were represented using a heat map. All frequency scores were calculated using the TF-IDF score. This is a way of measuring the importance of a term within a document relative to a set of documents. The TF-IDF scores a word by multiplying the term frequency (TF) of the word by the inverse document frequency (IDF) (Qaiser & Ali, 2018).

Finally, although the duplicates were located through their ID, many tweets were published with slight variations from others. For this reason, once the documents were cleaned, the tweets with slight variations in the text with respect to the original were also eliminated. After performing all the processing steps 1 to 6 described above, the resulting token strings were compared, and those with no variations were eliminated. This way, duplicate tweets that only presented differences in some punctuation marks, hyperlinks, or morphological variations in some words were eliminated. This was done because the present study aims to highlight the original messages produced by the spectators before the new technology implemented in soccer, video refereeing.

The collected tweets will only be used for research and non-commercial purposes, to comply with Twitter's terms of service. Furthermore, considering that the data retrieved are public and many users may be unaware of the relevance or further use of the data, the ethical recommendations

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proposed by Williams, Burnap, and Sloan (2017) were followed. In relation to informed consent, studies conducted in social networks and other online activities present great difficulties for the consideration of such issues. Thus, when it is not possible to obtain it, the analysis should be conducted only with depersonalized data. If researchers wish to cite comments made publicly, they should make reasonable efforts to seek the user's permission (Williams et al., 2017).

To establish the topics that emerged from the collection of tweets, a latent Dirichlet allocation (LDA) model was implemented, which assumes the existence of a fixed number of related latent topics that can appear with each downloaded tweet. Each topic is characterized by a discrete probability distribution over words; that is, the probability that a specific word is present in a text document depends on the presence of a latent topic (Blei, Ng, & Jordan, 2001; Büschken & Allenby, 2016).

Sometimes emojis appear in the text field of the tweet. In these cases, the emojis were extracted from the text of the tweets and stored separately. It is worth explaining that emojis are images or pictograms used to express an emotion, a feeling, or an idea, and are normally used in digital media to accompany a message. They can appear individually or in groups inserted anywhere in the text to reinforce or convey a parallel message to what is expressed in the document. A count was made of all of them, and the most repeated ones were graphically represented, using the Symbola.ttf font function for Unicode symbols. The most common meaning given by users was also searched using the Complete Emoji List, v13.0, which can be retrieved from the web unicode.org and emojipedia.org.

Analysis

The first step in analyzing the tweets involved describing the ad hoc-created database. The number of tweets per day, the most active accounts, and the tweets that received the most retweets were recorded. Additionally, a frequency analysis of the main unigrams and emojis was performed. The frequency values of the main unigrams, bigrams, and trigrams were represented by word clouds. In turn, an emoji cloud was used to represent the frequencies of emojis. To establish the growth and decline of the most cited words over the study period, the words were represented by a heat map. All frequency values were normalized using a z-score.

Occasionally, when a tweet is published, the author often mentions other users. This is usually done by including hyperlinks (hashtags, URLs, etc.) from other users or information sources. In the preprocessing phase, such hyperlinks were removed. However, they were stored. With this attribute, a mention network was constructed, in which nodes show the number of times an account was mentioned more than 600 times. To describe this network, the following centrality values were calculated using standard functions implemented in MATLAB: pagerank, authority rank, in-degree, in-degree weight, and in-closeness centrality (Borodin, Roberts, Rosenthal, & Tsaparas, 2005). This was done to establish the strength of each of the nodes or accounts within the mentioned network.

Results

In this study, 119,253 original tweets on VAR, football, and the Premier League have been retrieved from January 1 to May 10, 2021. Moreover, during this time, the tweets were retweeted 360,801 times, with April 11 being the day with the highest traffic of original tweets (6,809 tweets). The representation of dynamics by days in which the original tweets have been published is shown in Figure 3.

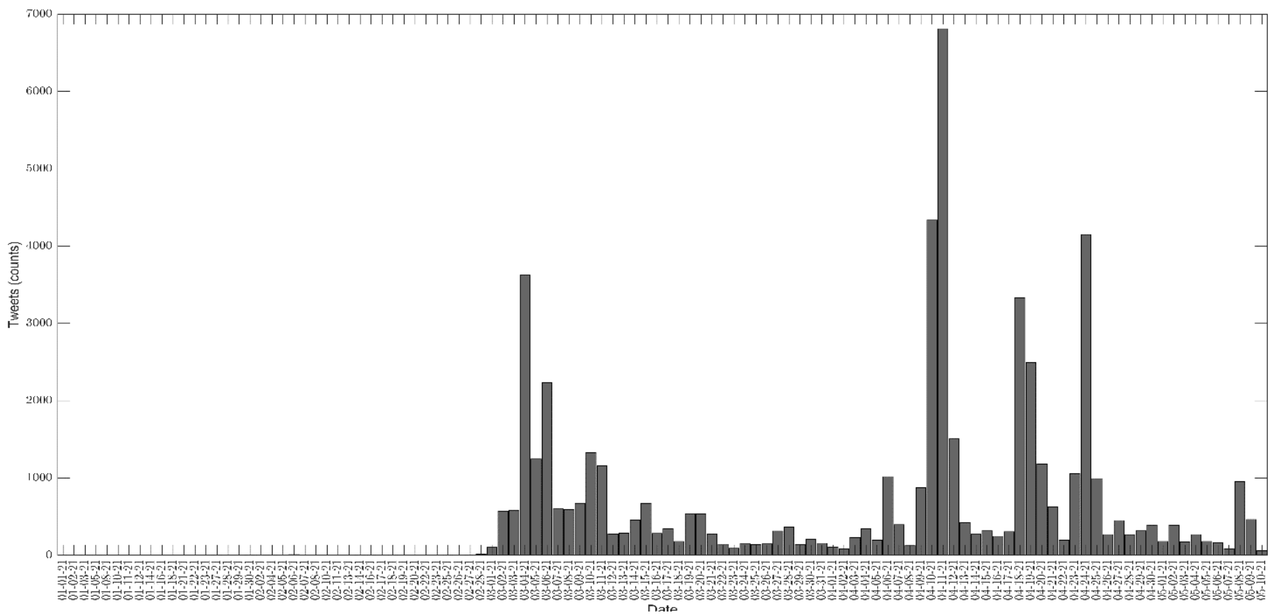

Figure 3. The number of tweets published about VAR, football, and the Premier League during the study period.

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Description of the Words Published in the Tweets (N-Gram) and Their Dynamics throughout the Study Period

The results of this study showed "var" (59,805), "football" (38,976), and "'referee" (14,091) as the most repeated words. These words formed part of the search strategy employed. Nevertheless, one of the objectives of our work was to point out the words associated with these three terms. Figure 4 shows the most repeated unigrams, bigrams, and trigrams in our file. Among the bigrams, "premier league" was most repeated (6,419). Finally, among the trigrams, the association between the words "var ruin football" (2,070) and "var kill football" (879) stands out.

In figure 5 shows the 30 most used words, during the study period, with their normalized values (z-score). In general, the dynamics of all the words throughout the study period are similar. That is, some words are not observed at a given moment and other words at a different moment in time. In Figure 5, four major moments of concentration of the most used words have been found, which coincide with the days when the most original tweets were collected (Figure 3). However, in the period from March 20 to the beginning of April the lowest values are shown (Figures 3 and 5). The most used 100 n-grams are listed in Table S1_ngrams

Figure 4. The unigrams, bigrams, and trigrams that were used most in the tweets recovered.

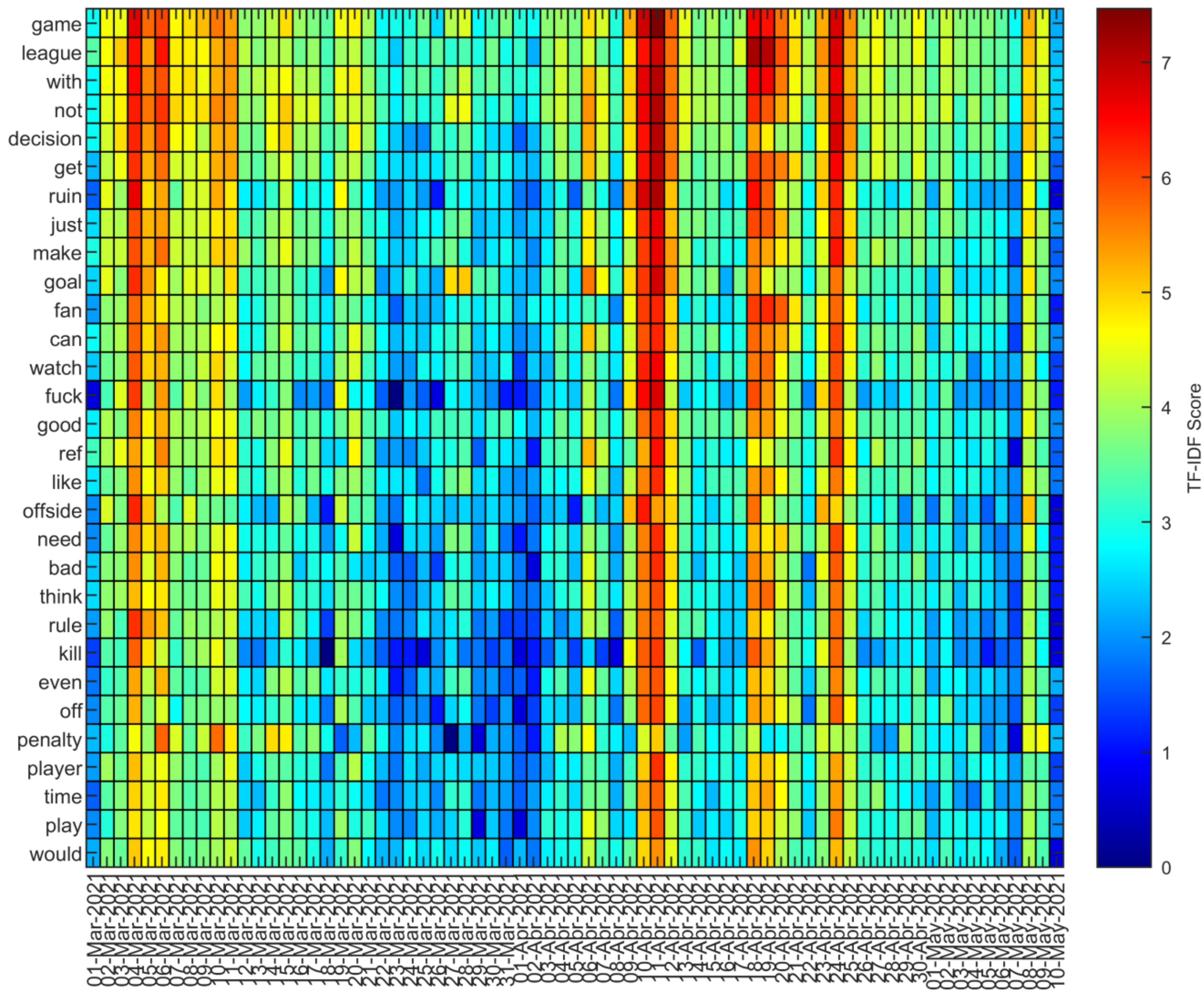

Figure 5. Dynamics of the 30 most repeated words during the study period.

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Network of Mentioned Entities

Usually, when users post a tweet, they mention some entities or persons to support or contradict their opinions or ideas. It generates a large network with high complexity and infinity of subnets, which have a high variable number of components. Furthermore, Figure 6 shows a high density of citations, which have 29 actors with more than 40 mentions.

The centrality values of the 20 main actors involved in this subnetwork are shown in Table S2_centrality values. The entities most mentioned correspond to sports and football private entities, such as @Sky Sports Premier League, @Sky Sports News, or @BBC Sports. Also, we find entities of individual people, such as @Gary Lineker, former professional footballer and current sports commentator, @Rio Ferdinand, former footballer, or @Adrian Durham, English football journalist and broadcaster. Moreover, some entities of English sports clubs appear, such as @Liverpool FC, @Manchester United or @Arsenal.

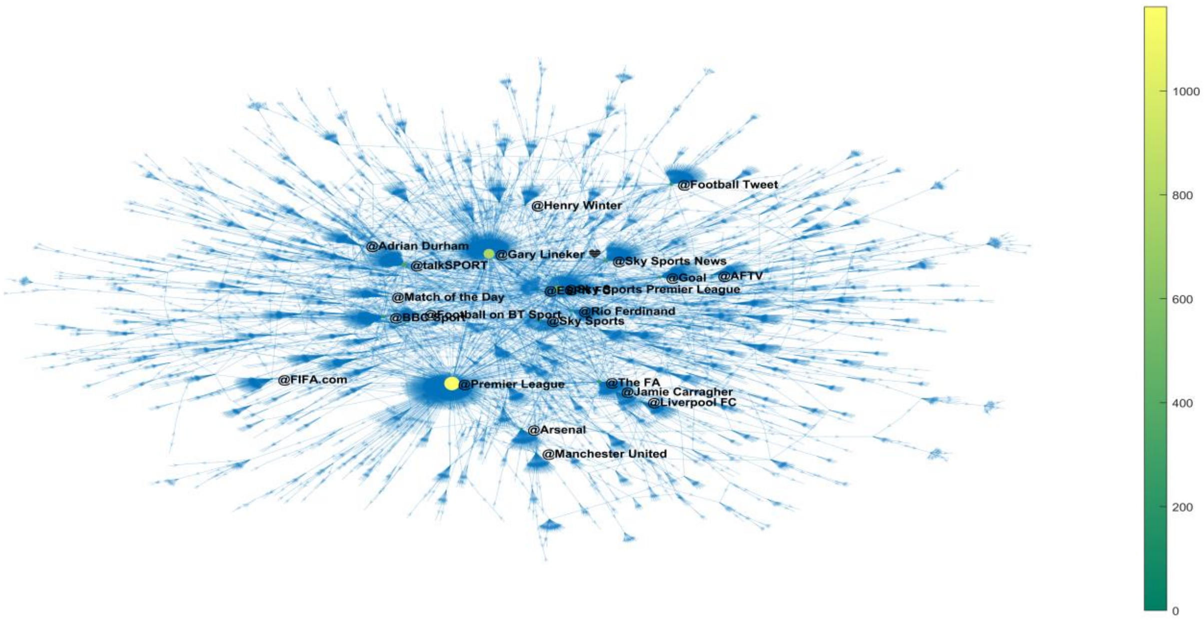

Figure 6. Subnet of mentions with a greater number of components.

Main Topics Found in the LDA Model

Through an LDA Model, a classification of words with 10 large topic groups was generated, which were composed of a group of words with an associated probability of appearing together. Furthermore, the order of clusters was from highest to lowest probability (Figure 7).

During the study period, the words observed in Figure 7 concern the users of Twitter and everybody, by extension. In this figure, any word could be displayed in different topics if it had a high probability of representing these topics. In addition, each cluster represents a topic, which shows a concern from people.

Emojis

Another descriptive result observed in this study is the emojis, which are used to complement the tweet or, independently, as a tweet in itself. These are used to express an opinion, thought, or feeling through an acronym or emoticon. These results are observed in Figure 8. In this figure we can see the emojis most used in these topics (the largest are more used in tweets than the smallest). In general, Figure 8 shows Laughing (2 emojis) and the ball of football as the most used. Last, other emojis also are used, such as sad face, loud crying face and face with symbols on the mouth (symbols represent an insult). It should be noted that, of the 20 most used emojis, only two (located in positions 12 and 13) have positive connotations about VAR, specifically clapping hands and one hand with the thumb up. Moreover, only the football ball emoji is neutral since it represents the same sport and is neither positive nor negative. The rest of the emojis (17 of 20) represent laughter, sadness, helplessness, rejection, boredom, or frustration, which show negative connotations towards VAR. It can be seen in Table S4_emojis frequency.

Figure 7. Representative words of the topics found in the LDA model. Words with a lower probability appear in a smaller size (Table S3_top_word_topic_LDA to see words with low probability).

Figure 8. Frequency of emojis in tweets, according to their size.

Discussion

The opinions and feelings of Twitter users about VAR in elite football have been studied from 1 January to 10 May 2021, following its recent implementation in this sport. Overall, our results showed a trend of negative opinions about VAR in elite football.

On the one hand, in terms of the number of daily tweets, four major moments or days are shown in which a higher number than usual were collected (Figure 3). Two days in April 2021 stand out: the 10th, when the Spanish La Liga match between Real Madrid and Barcelona was played; and the 11th, when the Premier League match between Tottenham and Manchester United was played. In both matches, the VAR intervened. In the first match in a penalty/non-penalty situation, and in the second match in a possible infringement committed by a player of the attacking team just before a goal was scored. The international relevance and the historic sporting rivalry between the teams (Carbonell, 2013; Chadwick & Arthur, 2008; Coteron Lopez & Bello Garrido, 2012) could have boosted the number of tweets that fans produced about VAR in those two matches. In the Spanish league match, in the final minutes and with the score in Real Madrid's favor 2-1, the referee did not consider that there was enough contact to award a penalty in Barcelona's favor. In the English league match on 11 May (the day on which the most tweets were collected), with the score at 0-0, the visiting team took the lead and celebrated a goal that was eventually disallowed by the VAR because it considered that there had been a previous foul.

On the other hand, as shown in the results, the words most often associated with mentioning the VAR in the form of bigrams were "ruin football" and "var ruin", and in the form of trigrams "var ruin football" and "var kill football" (Figure 4). These associations show how quite similar negative thinking is associated with the VAR.

As for the topics extracted with the LDA model, in topics 1 and 6, Twitter users expressed their disagreement with the arrival of the VAR, with the following words being the most likely to be associated with the VAR in both topics: "football", "fuck" and "ruin" (Figure 7). In topics 3, 7 and 10, users were observed sharing their opinion on the decisions made by the referee. In such a way many tweets are generated by Twitter users who are following the football matches and in turn issue an evaluation or judgement of some situations of the match on the network. Such as: whether a play with a player in an offside position should be disallowed or not, whether there is a penalty or not, whether the penalty deserves a red card or not, etc. These judgments and evaluations by the fans of both teams that are facing each other generate a debate on the net. This is very much in line with previous research carried out by Eagleman (2013) and Filo (2015) in which it is mentioned that social media is mainly used as a communication tool, highlighting from their findings the use of social networks to engage in discussions with and between fans/supporters. Regarding topic 5, it was observed how users express that VAR still has a lot of room for improvement, making a comparison with other sports such as rugby, where the decision-making process is open and public. Stoney and Fletcher (2021) have already highlighted the importance of fans receiving adequate information on the review process.

Through the results of the emojis, we have been able to obtain information about the emotions and feelings of Twitter users associated with the VAR topic. Most of the emojis with the highest usage are negative, generally representing mocking laughter, sadness, helplessness, rejection, boredom, or frustration, which is in line with a negative judgment towards the VAR. However, Winand et al. (2021) in a questionnaire study, concluded that there was mostly confidence in the work of the VAR, except for those fans who felt more identified with their team. In a similar vein is the work of Hamsund and Scelles (2021), who explained that most fans were happy with the implementation of VAR, but expressed that changes need to be made in terms of how it is used by referees on the field to assess certain situations.

These results are far from the negative idea reflected in the results obtained in the present work, which may be due to the different methodology and samples used. Scanlon et al. (2022) obtained results that are like those shown here. Their work explained that fans highlighted that VAR has had a negative impact on the match day atmosphere, while others underlined that VAR lacks communication between referees and fans present in the stadiums. In turn, these authors also concluded that VAR and the rules of the game need further harmonization to improve their consistency, noting that for some fans it indicates that innovation and technology are necessary.

This work also has some limitations. For example, we used English as the only language of the study, as it was the lingua franca on Twitter (Takhteyev, Gruzd, & Wellman, 2012). This choice reduces the number of users and tweets, particularly in non-English-speaking countries. Another limitation was that we only analyzed original tweets. Therefore, in future studies it would be interesting to replicate the same study to see if the opinion on VAR has changed or become more entrenched, as well as to include languages other than English and to analyze retweets instead of tweets.

This paper is the first to explore and represent the opinions and emotions of Twitter users about VAR in football, using the words expressed on social networks through a novel analysis. It concludes that Twitter users, for the time being, have a negative opinion and emotions about VAR in elite football.

Supplementary Materials

Table S1_ngrams; Table S2_centrality values; Table S3_top_word_topic_LDA; Table S4_emojis frequency.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

All the data are included in Supplementary Materials.

Conflicts of Interest

The authors declare no conflict of interest.

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