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How live Twitter commentaries by professional sports clubs can reveal intergroup dynamics☆

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ABSTRACT

Social media can both decrease and increase polarization between social groups. Communicative behaviors associated with intergroup conflict are ingroup favoritism and outgroup derogation. In the current paper, we propose that bias in social-media use can be assessed by focusing on live Twitter commentaries posted by sports clubs. Specifically, we focus on four bias types: biases in (1) communication volume, (2) balance, (3) fairness, and (4) recipient engagement. We analyzed Twitter commentaries placed by soccer clubs in the Dutch *Eredivisie* during the 2019/20 season (232 games, $N_{tweets} = 13{,}789$). Results on volume showed that clubs placed more tweets during wins (vs. draws or losses). For balance, we found that teams devoted a larger percentage of their feed to positive ingroup (vs. outgroup) events. For fairness, a larger proportion of positive ingroup (vs. outgroup) events were reported in the Twitter commentaries. Furthermore, fans engaged more with tweets about positive ingroup (vs. outgroup) events. By contrast, we did not find differences for negative ingroup (vs. outgroup) events for balance, fairness, or engagement. Taken together, our results show that sport clubs' live Twitter commentaries reflect ingroup favoritism, but not outgroup derogation.

1. Introduction

Social media can both decrease (Barberá et al., 2015) and increase polarization (Van Bavel et al., 2021). On the one hand, social media allow users to be exposed to different ideological positions on important issues, enabling them to see an issue from different sides, which can defuse polarization (Barberá et al., 2015; Eady et al., 2019). On the other hand, social media can separate users into ideologically homogeneous echo chambers and filter bubbles, which can amplify partisan messages and/or fake news, thereby increasing polarization (Banks et al., 2021; Levy, 2021; Van Bavel et al., 2021). This latter situation may, in turn, increase polarized positions and hostility towards those who hold a different position. When such polarized opinions dominate public discourse, the proper functioning of democracy may be at risk (Jost et al., 2022). In this way, social media can play an important role in polarizing rival parties in different contexts, ranging from politics (political parties) to sports clubs.

One explanation for such hostile intergroup dynamics can be found in social identity theory (SIT; Tajfel & Turner, 1986), which argues that people derive inherent value from being a member of specific social groups, and that people want to maintain a positive image of the social groups to which they belong ('in-groups'). To maintain this positive group identity, people typically show favoritism towards their in-groups. At the same time, they can be very critical of and hostile towards groups to which they do not belong ('outgroups'), especially if they perceive a strong rivalry with this outgroup. In-group members who display communicative behavior showing ingroup favoritism are typically seen as good group members (Assilaméhou & Testé, 2013). Similarly, the desire to conform to the norm of showing ingroup favoritism is an important driver for ingroup members (Iacoviello & Spears,

☆ Data, syntax and outputs are available through our page on the Open Science Framework (https://osf.io/c6wqy/).

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2021).

While scholars have found much support for ingroup and outgroup biases in communicative behavior in experimental research (e.g., Assilaméhou & Testé, 2013; Burgers et al., 2015; Iacoviello & Spears, 2021), the study of in-group biases in real-life communication, like actual (social) media content, is scarce and much more complex. Many real-life situations involve complex intergroup dynamics in which various groups may be involved. In addition, the target situation and its valence may be difficult to determine (i.e., positive or negative for which group?), and it may not always be straightforward with which group senders of (social-media) messages identify themselves. Furthermore, it is often extremely difficult to determine what constitutes an objective (vs. subjective) description of a social situation, and thereby to determine whether and how an article or social-media post is biased (McLeod et al., 2017, p. 46). To resolve this issue, previous research has focused on the valence of specific online comments and the engagement they created in online communities (e.g., Harel et al., 2020; Marchal, 2022). However, in this approach, it is difficult to compare across posts, as these often involve different actors commenting on different situations, which prevents a fair comparison between groups to reveal biased communication. Thus, in many cases, analyzing intergroup bias in real-life communicative data is very complex.

In the current paper, we propose that the way sports clubs report on their games on social media provides a good real-life context to assess intergroup bias. After all, many sports clubs use social media to communicate directly to their fans (Price et al., 2013), and sports games meet the different criteria of intergroup situations. First, they involve fans who often strongly identify with their own club (Kerr & Wijeratne, 2021) and experience intergroup rivalry with their opponents (Haridakis, 2012). This intergroup rivalry likely triggers intergroup behaviors (Kim & Na, 2020). Second, the involved groups in a game can be identified clearly, as most sports games involve two teams to which intergroup behaviors can be linked (Burgers et al., 2015). Third, the situations are clear, as a game constitutes an event with a clear beginning and end, and, for many professional games, statistics are available that demonstrate how each team performed, allowing for a comparison across multiple games (Braun et al., 2021; Castellano et al., 2012). Fourth, the social media posts by both groups involved are available across the entire game period, allowing for a comparison of perspectives of both involved groups (i.e., the teams) on the same intergroup situation (i.e., the game).

In the following, we focus on two aspects that may reflect biased reporting on social media: (1) the use of social media by sports clubs and (2) the ways in which fans engage with these social-media messages of their clubs. We specifically focus on live commentaries of specific games placed by sports clubs on social media. In this way, we investigate whether and how SIT dynamics are expressed in these live Twitter commentaries, which provides more insights into intergroup dynamics in a naturalistic social-media setting. Our study also reveals reporting and engagement dynamics in this relatively new online genre of live Twitter commentaries. In the next sections, we focus on these different aspects, and present our hypotheses, after which we report on a content analysis of one season of play-by-play tweets placed by professional Dutch soccer clubs and the online engagement they generated.

1.1. Social media, sports clubs, and intergroup processes

The use of social media by professional sports clubs has profoundly changed the nature of sports journalism, and the relationship between clubs, fans and journalists (Sherwood et al., 2017). Where sports clubs traditionally relied on journalists to disseminate team news, they can now use social media to communicate directly to their fans (Price et al., 2013). As a result, traditional news media have become less important in distributing sports information to online communities (Vermeer & Araujo, 2020). In addition, many sports clubs use social media like Twitter as a one-directional broadcast medium (Cable & Mottershead, 2018), which means that they primarily use social media to send information to fans and other stakeholders, and less to engage in dialogue with these stakeholders.

One of the ways in which sports teams can use their social media presence is by providing live commentaries on their games. Such live commentaries provide an overview of events while the match unfolds. For fans who follow the game on social media, these live commentaries can be seen as narratives that structure the game (Jucker, 2010). Research has demonstrated that following a game via such live commentaries has increasingly become accepted among sports fans, particularly when using the live commentaries as a second screen next to a radio or TV broadcast (Ojomo & Olomojobi, 2021). Furthermore, sports fans typically consume live commentaries on social media because of utilitarian motivations, like the commentary's perceived usefulness and ease of use (Ojomo & Olomojobi, 2021).

Live commentaries in social media (e.g., in tweets) share important features with live commentaries in traditional mass media, like radio and television. Jucker (2010) demonstrates that live commentaries in social media and in traditional mass media follow a strict iconicity in that they typically focus on specific types of events during the game (e.g., goals, shots, yellow and red cards), and narrate these events in a chronological order. In addition, in both cases, the narration extends over the same time period as the game time.

Nevertheless, live commentaries on social media also differ in crucial ways from traditional outlets. Radio commentaries present a fluent narration of events: they typically feature minimal gaps in the narration and report on events within seconds of occurring. By contrast, the narration in live social-media commentaries can be less fluent, because they can feature more extensive gaps of multiple minutes between posting of individual messages. Thus, more time may have elapsed between an event happening on the field and it being reported in the live commentary on social media (Jucker, 2010). This also implies that sports clubs posting live commentaries on social media have more freedom in choosing which events to report and which to leave out of their commentaries. We expect that clubs' decisions to include or exclude particular events from their live commentaries can be driven by intergroup dynamics.

Interestingly, one of the earliest and well-known studies to document intergroup bias focused on group members' perceptions of a sports game. In their paper, Hastorf and Cantril (1954) discussed a controversial American college football game between Dartmouth and Princeton. The game was won by Princeton, but was also rough, with players from both sides having to leave the pitch after being injured, including Princeton's star player. Hastorf and Cantril (1954) found that the impression of this game differed widely between viewers affiliated with both universities. While nearly all Princeton students perceived the game as "rough and dirty", Dartmouth students, by contrast, perceived the game as "clean and fair" (over 10%) and "rough and fair" (over 33%). Similarly, Princeton (vs. Dartmouth) students perceived more fouls by Dartmouth players. These results demonstrate that having strong connections to a sports team can bias perceptions of games featuring this team.

SIT (Tajfel & Turner, 1986) proposed that group membership is an important part of individuals' social identities. According to SIT, two basic motivations guide social-identity processes: self-enhancement and uncertainty reduction. Both motivations are cued by intergroup social comparisons, indicating that group members strive to perceive their own group ('in-group') as better than and distinct from other rival groups ('out-groups'). SIT argues that, in these social comparisons, ingroup members often display favoritism towards their in-group and derogate outgroups and their members (Tajfel & Turner, 1986).

Previous research demonstrated that group members expect others to conform to these norms of ingroup favoritism and outgroup derogation. For an individual group member, being recognized as biased towards the ingroup boosts their intragroup approval (Assilaméhou-Kunz et al., 2020). Thus, for ingroup members, the desire to conform to this group norm is an important driver of their behavior (Iacoviello & Spears, 2021).

One of the goals of sports clubs for using social media is to increase engagement with their online fan base (Vale & Fernandes, 2018). Previous studies indicate that particularly reporting on negative events and losses for the in-group may lead to fans evaluating a match report negatively (Arpan & Raney, 2003; Kim & Billings, 2017). By stressing events that are positive for the ingroup, and downplaying negative events, a club can thus display ingroup favoritism and increase approval and engagement from their ingroup fans (cf. Assilaméhou & Testé, 2013). In live commentaries on social media, clubs can show ingroup favoritism by being more active during matches that move in a favorable direction (wins), while they can be more restrained and refrain from posting during matches that are more unfavorable (losses or draws). This leads to:

H1. Clubs place more social-media posts during wins than during (a) losses and (b) draws.

Besides differences in the volume of posts in intergroup situations with different outcomes (e.g., wins vs. losses), intergroup biases may also manifest themselves in the content of posts. Different ways to analyze content bias in a journalistic setting relate to the concepts of balance and fairness (McLeod et al., 2017). In the balance perspective, bias occurs if a particular news medium includes "coverage that systematically favors one side with more prominence and attention" (Zeldes et al., 2008, p. 563). In such studies, scholars thus investigate whether or not a particular news medium contains an equal amount of favorable and unfavorable arguments and sources covering both sides involved (see Lewis & Cushion, 2019; Schaefer & Fordan, 2014; Zeldes et al., 2008). In this case, the analysis of media content and/or sourcing can demonstrate in which way a particular outlet is biased.

Following the logic of SIT (Tajfel & Turner, 1986), we expect a bias in balance to occur in live social-media commentaries. That is, we expect that, during the game, social-media posts will display a pattern of ingroup favoritism and outgroup derogation, leading to our hypothesis on bias in balance of social-media content:

H2a. Live commentaries by clubs on social media contain relatively more posts about positive ingroup (vs. outgroup) events.

H2b. Live commentaries by clubs on social media contain relatively fewer posts about negative ingroup (vs. outgroup) events.

The balance perspective assumes that equal amounts of coverage for all sides involved leads to a fair discussion of the issue. However, in many cases, unbiased reporting goes beyond equal coverage for both sides, given that the truth of a matter may not necessarily lie in the middle (Boudana, 2016). For instance, if news outlets give equal weight to reports on the scientific consensual view on a matter and to fringe views that challenge this consensus, the news report may suggest that these two views are equivalent (Boykoff & Boykoff, 2004). Similarly, in sports coverage, a match is often more positive for one team than the other. If the home team had twenty shots on target and the away team had only one shot on target, we would expect a non-biased report to describe more shots by the home (vs. away) team. Thus, an alternative way to focus on bias is to analyze fairness, i.e., to which degree a report accurately represents activities of all parties as they occurred in reality (see also Boudana, 2016).

In many cases, this perspective on fairness is difficult to investigate in a way that generalizes over cases. After all, the meaning of perceptual events may differ among stakeholders (Hastorf & Cantril, 1954). In many contexts, it is hard to objectively ascertain how the involved parties behaved, whether this was positive or negative, and whether and how communicative messages divert from this pattern. However, sports reporting may be an exception to this situation, because sports games follow a clear set of rules. Furthermore, sports scientists propose that at least some happenings (e.g., goals, shots, and fouls) can typically be seen as meaningful and important game events (e.g., Castellano et al., 2012; Lago-Peñas et al., 2010). Some events can objectively be seen as positive for the team (e.g., goals and shots), while others as objectively negative for the team (e.g., fouls committed). Furthermore, these specific events are included in impartial match statistics that, at least for many professional sports games, are often freely available. Thus, we propose that fairness bias in live commentaries on social media can be measured by contrasting the number of reported events of some type (e.g., shots) with the total number of occurrences of that event type included in the match statistics. This may then reveal whether particular types of events are over- or under-reported in the commentary.

Thus, for bias in fairness, we again expect that live commentaries on social media show a pattern of ingroup favoritism, indicating that a larger proportion of actual positive events for the own team (vs. opponent) are mentioned and a smaller proportion of actual negative events for the own team (vs. opponent). This leads to our hypothesis on bias in fairness of social-media coverage:

H3a. Live commentaries by clubs on social media cover a higher proportion of all positive ingroup (vs. outgroup) events.

H3b. Live commentaries by clubs on social media cover a lower proportion of all negative ingroup (vs. outgroup) events.

1.2. Fan responses: BIRGing and CORFing

In *H1-3*, we focused on potential biases in social-media posts placed by sports clubs during games. In addition, we expect biases in the engagement of fans with these posts, given that intergroup processes may play an important role in fan responses to sports reporting. For instance, Arpan and Raney (2003) demonstrated that US sports fans perceived articles discussing games as negatively biased against their own team, especially when they were printed in newspapers published in neutral or rival towns. In addition, Kim and Billings (2017) showed that perceptions of bias in sports reporting of national teams were stronger when the own team lost (vs. won), particularly when the report was published in a foreign newspaper. These studies show that sports fans can have a negative stance towards news reporting on their team, especially if it features negative events for their own team and can be attributed to an outgroup source.

Research from the area of sports psychology describes that fans often engage in two specific types of behaviors that can reflect bias: (1) basking in reflected glory (BIRGing) when their team wins (Cialdini et al., 1976) and (2) cutting off reflected failures (CORFing) when their team loses (Hirshon, 2020). BIRGing implies that fans who identify with a sports team like to associate themselves with its successes, for instance by wearing a team jersey, by vocally expressing their support for the team or by watching game highlights when they already know that their team has won (Cialdini et al., 1976; Giles & Stohl, 2016). Another aspect of BIRGing includes fans referring to the team with self-inclusive references like 'we' (as in: "We won the game today"). By doing so, BIRGing fans frame themselves as being part of the team they support, which can foster self-esteem by transforming the success of the team into a personal success of the fans (Giles & Stohl, 2016). BIRGing is also expressed when fans attribute team success to internal factors of the team (e.g., "Our squad is very strong"), but attribute team failure to incidental contextual factors outside of the team's control (e.g., "The referee made some very bad calls against our team today"). Another way for fans to publicly identify themselves with their club is by liking or commenting on specific social-media posts related to the club. Following the BIRGing phenomenon, we expect that fans express more engagement (e.g., likes and retweets) with the social-media feed of their club with positive ingroup (vs. outgroup) events.

CORFing is the opposite behavior to BIRGing, and implies that fans (temporarily) disassociate themselves from their team in case of failures, for instance by not publicly identifying with the team (Haridakis, 2012). CORFing is also reflected by fans referring to the team with self-exclusive references like "they" (as in: "They lost the game today"), which implies that they see themselves as distinct from the team. Thus, in the case of negative team events, we expect fans to refrain from expressing online engagement with their team.

Another fan strategy to emphasize the positive distinctiveness of their team is blasting, in which fans derogate rival clubs and their fans (outgroup members; Haridakis, 2012). In contexts of political communication, research has demonstrated that animosity towards outgroups can drive engagement on social media (Rathje et al., 2021). That is, negative posts about outgroups are more often shared online and are likeliest to go viral. In the case of sports, schadenfreude at the misfortune of rival teams may drive group behavior. For instance, Ouwerkerk and van Dijk (2014) describe how, during the FIFA 2010 World Cup, many Dutch viewers switched their TV to the German broadcast when their traditional rival Germany conceded a crucial goal. Following the blasting phenomenon, we expect that fans express more online engagement with negative outgroup events.

In sum, we expect that intergroup dynamics drive the way in which fans engage with positive and negative posts about the ingroup and outgroup, which leads to:

H4a. Tweets about positive ingroup (vs. outgroup) events receive more online engagement.

H4b. Tweets about negative ingroup (vs. outgroup) events receive less online engagement.

2. Method

2.1. Sampling

This study examined live commentaries placed by sports clubs on Twitter. Specifically, we focused on Dutch soccer teams playing in the *Eredivisie*, the highest tier of professional men's soccer in the Netherlands. We zoomed in on soccer, because it is the most popular sport in the Netherlands, with the highest membership rate in the country (NOC*NSF, 2019). Furthermore, Twitter accounts are an important means for *Eredivisie* clubs to reach and engage with their fan base (Vermeer & Araujo, 2020). In the target season of this study (2019–2020), all clubs in the *Eredivisie* placed live commentaries of their own games on their Twitter accounts. For each match, we thus included the commentaries of both sides. In addition, official match statistics were available for every game to provide objective information about the games played.

The *Eredivisie* contains eighteen teams. In a regular season, each team plays against every other team twice: once in a home game and once in an away game. Because of the global COVID-19 pandemic, the *Eredivisie* season 2019/2020 was cancelled after twenty-six (out of thirty-four) rounds of play (MacInnis & Lowe, 2020). In total, 232 (out of the usual 306) games of the season were completed and analyzed.[1]

We scraped all tweets sent by the official Dutch-language Twitter accounts of all eighteen *Eredivisie* clubs, using the *R* package *rtweet* (Kearney, 2019). Tweets sent between August 2, 2019 (the first day of the season) and March 8, 2020 (the last match day before the season ended) were included. Table 1 contains descriptive information of the teams involved.

Twitter accounts from sports clubs can serve various functions, such as providing news, presenting opinions, engaging in community relations, and marketing/sales (Williams et al., 2014). In our analysis, we were only interested in live commentaries and only included tweets that were (a) placed during a game, and (b) commented in some way upon the ongoing game. For each game, we manually coded tweets announcing the start of the game as the first match tweet, and tweets announcing the final result as the last match tweet. In addition, we only included live commentaries of *Eredivisie* games, and excluded games played by *Eredivisie* clubs in other competitions and/or settings (e.g., the Dutch *KNVB Cup*, European competitions like the *UEFA Champions League* or *Europa League*, and friendly games). For every game, we included the live Twitter commentaries from both clubs, resulting in a corpus containing 464 Twitter commentaries, consisting of 13,789 tweets in total. Please note that our corpus is completely counter-balanced, because, for each game, the Twitter commentaries of both clubs involved were included.

Official objective match statistics were compiled by Opta Sports (n.d.), and were retrieved from the website of Voetbal International (n.d.), the largest independent soccer magazine in the Netherlands.

2.2. Measures

To test *H1* on volume, we determined *Tweet volume* by counting the number of tweets that were placed by a club during each match (M = 29.72, SD = 8.88).

Next, we manually coded for the mentioning of positive and negative ingroup and outgroup events in the tweets. All shots (i.e., goal attempts) were considered as *Positive events*, and all fouls and offsides[2] were seen as *Negative events*. Shots, fouls and offsides are common match events in soccer, which are also included in the official match statistics (Castellano et al., 2012). Events initiated by the team posting the tweet (e.g., the tweeting team made a shot, made a foul or was offside) were considered *Ingroup events*. When an event was initiated by their opponent (e.g., the opponent placed a shot, made a foul or had a player offside), it was considered an *Outgroup event*.

Please note that we included the live Twitter commentaries of every team and match played, and that an ingroup event for one club was an outgroup event for their opponent. To illustrate, consider a shot on target by an Ajax player during the game Ajax vs. Feyenoord. If this shot was mentioned in the Twitter commentary of Ajax, it was coded as a positive ingroup event. If this same shot was mentioned in the Twitter commentary of Feyenoord, it was coded as a positive outgroup event.

We conducted an intercoder reliability test on 10% of the data (24 games; 1395 tweets), following recommendations by Wimmer and Dominick (2011, p. 172). For these games, the Twitter commentaries of both clubs were independently evaluated by two coders (the third and fourth authors of the paper). Intercoder reliability was assessed with the *irrCAC* package for *R* (Gwet, 2019). We found that, for each category, Krippendorff's α was higher than the critical value of 0.80 (Krippendorff, 2013), indicating that our coding was reliable (positive ingroup events: Krippendorff's $\alpha = 0.87$; positive outgroup events: Krippendorff's $\alpha = 0.93$; negative ingroup events: Krippendorff's $\alpha = 0.88$; negative outgroup events: Krippendorff's $\alpha = 0.85$).

From these codings, we calculated different measures. To test *H2* on balance, for each match, we calculated the proportion of tweets mentioning positive and negative events for the ingroup and outgroup. We did so by dividing the number of tweets about specific types of events in a particular game (positive ingroup, positive outgroup, negative ingroup, negative outgroup) by the total number of tweets in the specific commentary.

To test *H3* on fairness, we assessed to which degree all actual events of different types were mentioned in the commentary. We calculated the *Proportion of Events Tweeted*. For this measure, we used the official game

[1] Two games (AZ – Feyenoord and Ajax – FC Utrecht) were originally scheduled for 9 February 2020, but were cancelled due to extreme weather. Because the rescheduled date was later than the day on which the entire season was cancelled, these games were never played (KNVB Media, 2020). This explains why these four teams played 25 games, while all other teams played 26 games.

[2] For particularly impactful fouls, players can receive a yellow or red card. To prevent these fouls from being counted twice, we based the total number of negative events on fouls and offsides.

Table 1
Descriptive information of the clubs involved in the Dutch Eredivisie (season 2019–2020).

Pos	Club	City	Twitter handle	P	Pts	GD	Tweet volume	Tweets per game	Twitter followers
1	Ajax	Amsterdam	AFCAjax	25	56	+45	587	23.48 (5.55)	1,243,762
2	AZ	Alkmaar	AZAlkmaar	25	56	+37	594	23.76 (4.80)	70,083
3	Feyenoord	Rotterdam	Feyenoord	25	50	+15	594	23.76 (5.10)	473,784
4	PSV	Eindhoven	PSV	26	49	+26	441	16.96 (2.39)	459,418
5	Willem II	Tilburg	WillemII	26	44	+3	1288	49.54 (7.66)	38,435
6	FC Utrecht	Utrecht	fcutrecht	25	41	+16	863	34.52 (5.23)	70,762
7	Vitesse	Arnhem	MijnVitesse	26	41	+10	798	30.69 (4.74)	68,016
8	Heracles Almelo	Almelo	HeraclesAlmelo	26	36	+6	777	29.88 (7.55)	29,352
9	FC Groningen	Groningen	FCGroningen	26	35	+1	697	26.81 (4.31)	80,835
10	SC Heerenveen	Heerenveen	scHeerenveen	26	33	0	800	30.77 (3.58)	81,463
11	Sparta Rotterdam	Rotterdam	SpartaRotterdam	26	33	−4	791	30.42 (5.25)	24,610
12	FC Emmen	Emmen	FC_Emmen	26	32	−13	795	30.58 (4.37)	15,388
13	VVV-Venlo	Venlo	VVVVenlo	26	28	−27	1030	39.62 (8.13)	27,506
14	FC Twente	Enschede	fctwente	26	27	−12	690	26.54 (6.34)	124,864
15	PEC Zwolle	Zwolle	PECZwolle	26	26	−18	778	29.92 (5.79)	67,717
16	Fortuna Sittard	Sittard	FortunaSittard	26	26	−23	805	30.96 (5.47)	17,629
17	ADO Den Haag	The Hague	ADODenHaag	26	19	−29	572	22.00 (4.81)	66,025
18	RKC Waalwijk	Waalwijk	RKCWAALWIJK	26	15	−33	889	34.19 (4.80)	19,516

Note: Pos = Position in the Eredivisie, P = Games played, Pts = Points won, GD = Goal Difference (i.e., Number of goals scored – number of goals conceded). Teams are listed in order of their league position when season ended. The Tweet volume column indicates the total number of tweets in the corpus per club. The 'Tweets per game' column indicates the mean (and standard deviation) of the number of tweets sent per Eredivisie game. The Twitter followers column lists the number of followers at the start of the first game of the Eredivisie, season 2019–2020.

statistics as a baseline, which also contained totals of shots (positive events), fouls and offside (negative events) per team. For instance, to calculate the proportion of positive in-group events, we divided the number of tweets mentioning positive ingroup events by the total number of positive ingroup events according to the official match statistics. In some cases, specific events were tweeted about more than once. We also calculated the *Proportion of Unique Events Tweeted* in which every event was counted only once, also when this event was mentioned in multiple tweets from the same commentary.

To test *H4* on engagement, we included *Favorites* and *Retweets* as measures of *Online Engagement* (Shermak, 2018). For each tweet, the number of *Favorites* and *Retweets* was automatically extracted during scraping. We then calculated the mean number of favorites and retweets for tweets mentioning the different types of events (positive ingroup, positive outgroup, negative ingroup, negative outgroup). Because the number of Twitter followers differed strongly between individual clubs (see Table 1), engagement scores were standardized per 10,000 followers. In cases in which clubs did not tweet about certain types of events during a particular game, we coded engagement scores as missing values.[3]

Online Appendix A (see https://osf.io/c6wqy) shows means and standard deviations for all individual teams on the measured variables. An inspection of the engagement variables demonstrated a long-tail distribution (see Online Appendix B, https://osf.io/c6wqy), which is why we transformed the data and ran our analyses for *H4* on the log(1 + x) engagement data.

2.3. Data analysis

Data were analyzed with *R*, version 4.0.5 (R Core Team, 2021), using the packages *tidyverse* (Wickham et al., 2019), *readxl* (Wickham & Bryan, 2019), *tableHTML* (Boutaris et al., 2021), *htmltools* (Cheng et al., 2021), *psych* (Revelle, 2021), *lme4* (Bates et al., 2015), *sjPlot* (Lüdecke, 2021), and *TouRnament* (Wolfanger, 2019). Table 1 reveals that individual clubs differed in the number of tweets they posted on average during a match, with the highest club average of tweets per game (Willem II) being 2.91 times higher than the lowest club average of tweets per game (PSV). To compensate for these random differences in tweet behavior on the club level, we conducted linear mixed-effects analyses with club as a random variable. A visual inspection of residual plots revealed no obvious deviations from normality or homoscedasticity for any of the analyses (see Online Appendix C at https://osf.io/c6wqy).

3. Results

H1 proposed that clubs would place more tweets during wins than during (a) losses or (b) draws. Table 2 contains the results of the linear mixed effects analysis. Pairwise comparisons with Bonferroni adjustment demonstrated that clubs indeed placed more tweets during wins (M_{win} = 31.48, SE_{win} = 1.77)[4] compared to draws (M_{draw} = 29.38, SE_{draw} = 1.81; t(449.13) = 3.07, p = .007) and losses (M_{loss} = 28.04, SE_{loss} = 1.77, t(450.49) = 5.82, p < .001), supporting H1. We found no

Table 2
Fixed-effects estimates and variance–covariance estimates for the model predicting tweet volume.

	Tweet volume		
Predictors	Estimates	99%CI	p
(Intercept)	31.48	27.05–35.92	<.001
Result [Draw]	−2.10	−3.86–−0.34	.002
Result [Loss]	−3.44	−4.96–−1.92	<.001
Random Effects			
σ^2	28.10		
$\tau_{00\ Team}$	50.46		
ICC	0.64		
N_{Team}	18		
Observations	464		
Marginal R^2/Conditional R^2	0.029/0.653		

Note. The reference category for the Result predictor was a Win. The random effects part reports the within-group variance (σ^2), between-group variance (τ_{00}), the Intraclass Correlation Coefficient (ICC), and the number of units in a group (N). Model fit is reported for both marginal and conditional R^2.

[3] The number of commentaries with missing values for engagement scores were as follows: positive ingroup events: 1; positive outgroup events: 9: negative ingroup events: 106; negative outgroup events: 112.

[4] Here, we report the estimated marginal means, which are corrected for the difference in tweet behavior of the individual teams. Table A1 in Online Appendix A (https://osf.io/c6wqy) shows the raw means per club.

difference in the volume of tweets posted during losses and draws (t (448.83) = 1.97, p = .15).

Table 3 reports descriptive statistics and Table 4 contains results of the linear mixed effects analyses for *H2-4*.[5] *H2* assessed potential bias in balance, and predicted an interaction between target club (ingroup vs. outgroup) and event valence (positive vs. negative) on tweet behavior in that a higher proportion of tweets would contain positive ingroup (vs. outgroup) events (*H2a*). At the same, we expected that a smaller proportion of tweets would focus on negative ingroup (vs. outgroup) events (*H2b*). The analysis reveals a main effect of event valence, but not of target club, indicating that Twitter live commentaries focus more on positive than negative events ($M_{positive}$ = 0.26, SD_{positive} = 0.14, $M_{negative}$ = 0.06, SD_{negative} = 0.05). More importantly for *H2*, we found a significant interaction effect of target club and event valence. Post-hoc comparisons with Bonferroni adjustments indicate that a higher proportion of tweets focuses on positive ingroup (vs. outgroup) events (t(1841) = 22.76, p < .0001), supporting *H2a*. However, we find no differences between negative ingroup and negative outgroup events (t(1841) = 0.60, p = .55), which implies that *H2b* is not supported by the data.

H3 focused on potential bias in fairness, and predicted that clubs would (a) mention a higher proportion of actually occurred positive ingroup (vs. outgroup) events, but (b) a lower proportion of actually occurred negative ingroup (vs. outgroup) events. Results mirror those of *H2*. Again, we found a main effect of event valence, but not of target club, indicating that Twitter live commentaries reported a higher proportion of positive than negative events (proportion of events tweeted: $M_{positive}$ = 0.59, SD_{positive} = 0.33, $M_{negative}$ = 0.15, SD_{negative} = 0.13; proportion of unique events tweeted: $M_{positive}$ = 0.51, SD_{positive} = 0.26, $M_{negative}$ = 0.15, SD_{negative} = 0.12). Similar to *H2*, we found interaction effects of target club and event valence. Post-hoc comparisons with Bonferroni adjustments reveal that live Twitter commentaries include a higher proportion of positive ingroup (vs. outgroup) events (proportion total events tweeted: t(1841) = 23.59, p < .0001; proportion unique events tweeted: t(1841) = 19.19, p < .0001), which supports the predictions in *H3a.* Again, analyses reveal no differences between negative ingroup and outgroup events (proportion events tweeted: t(1841) = 0.34, p = .73; proportion unique events tweeted: t(1841) = 0.45, p =

Table 3
Means (and Standard Deviations) of the Proportion of Tweets with Events, Proportion of Events Tweeted, Proportion of Unique Events Tweeted, and the number of Favorites and Retweets per tweet, by event valence (negative, positive) and type of situation (ingroup, outgroup).

	Negative		Positive	
	Ingroup	Outgroup	Ingroup	Outgroup
Proportion of Tweets with Events	0.06 (0.05)	0.06 (0.05)	0.33 (0.13)	0.19 (0.10)
Proportion of Events Tweeted	0.15 (0.13)	0.15 (0.13)	0.75 (0.33)	0.44 (0.24)
Proportion of Unique Events Tweeted	0.15 (0.12)	0.14 (0.12)	0.61 (0.26)	0.40 (0.21)
Favorites	0.92 (8.58)	0.43 (0.50)	2.22 (4.15)	0.50 (0.68)
Retweets	0.16 (1.68)	0.05 (0.12)	0.37 (0.98)	0.07 (0.12)

Note: Proportions are coded from 0 to 1, with 1 indicating higher proportions. The numbers of Favorites and Retweets are standardized per 10,000 followers. Even though this table reports unstandardized means (and standard deviations), analyses for Favorites and Retweets were conducted on the log(1 + x)-transformed dataset.

[5] Table 4 reports the models with main effects and interaction effects. In Online Appendix D (https://osf.io/c6wqy), we also present the outcomes of the empty models and the models with only main effects.

Table 4
Fixed-effects estimates and variance–covariance estimates for the models predicting balance (H2), fairness (H3) and engagement (H4).

	Proportion Tweets with Event			Proportion Events Tweeted			Proportion Unique Events Tweeted			Favorites			Retweets		
Predictors	B	99%CI	p	B	99%CI	p	B	99%CI	p	B	99%CI	p	B	99%CI	p
(Intercept)	0.06	0.05–0.07	<.001	0.15	0.09–0.20	<.001	0.14	0.08–0.20	<.001	1.75	1.10–2.39	<.001	0.53	0.04–1.03	.006
Target club	0.00	−0.01 – 0.02	.550	0.00	−0.03–0.04	.732	0.00	−0.02 – 0.03	.651	−0.09	−0.29 – 0.11	.247	0.09	−0.09 – 0.27	.199
Event valence	0.14	0.12–0.15	<.001	0.29	0.25–0.32	<.001	0.26	0.23–0.29	<.001	0.81	0.62–1.00	<.001	0.46	0.29–0.62	<.001
Group type * event valence	0.13	0.11–0.15	<.001	0.31	0.26–0.36	<.001	0.20	0.16–0.24	<.001	1.76	1.49–2.03	<.001	1.38	1.15–1.62	<.001
Random Effects															
σ^2	0.01			0.04			0.03			1.10			0.84		
τ_{00}	0.00_{Team}			0.01_{Team}			0.01_{Team}			1.08_{Team}			0.63_{Team}		
ICC	0.01			0.15			0.22			0.50			0.43		
N	18_{Team}			18_{Team}			18_{Team}			18_{Team}			18_{Team}		
Observations	1856			1856			1856			1628			1628		
R^2 mar/con	0.605/0.608			0.557/0.624			0.519/0.627			0.336/0.665			0.300/0.600		

Note: Proportions are coded from 0 to 1. Analyses for engagement (Favorites and Retweets) were conducted on the log(1 + x)-transformed dataset. The reference category for Target club was the outgroup, and the reference category for Valence was negative events. The random effects part reports the within-group variance (σ^2), between-group variance (τ_{00}), the Intraclass Correlation Coefficient (ICC), and the number of units in a group (N). Model fit is reported for both marginal (mar) and conditional (con) R^2.

.65), indicating that *H3b* was not supported.[6]

Next, we tested *H4*, which predicted an interaction between group type and event valence on online engagement (favorites and retweets), in that tweets about positive ingroup (vs. outgroup) events would receive more engagement, while tweets about negative ingroup (vs. outgroup) events would receive less engagement. Table 4 shows main effects for event valence, but not for target club. Tweets about positive events received more engagement than tweets about negative events (favorites: $M_{positive} = 1.37$, $SD_{\text{positive}} = 3.11$, $M_{negative} = 0.68$, $SD_{\text{negative}} = 6.11$; retweets: $M_{positive} = 0.22$, $SD_{\text{positive}} = 0.72$, $M_{negative} = 0.10$, $SD_{\text{negative}} = 1.20$). We also found an interaction of target club and event valence. Post-hoc comparisons with Bonferroni adjustments indicate that tweets about positive ingroup (vs. outgroup) events received more engagement (favorites: $t(1613) = 24.06$, $p < .0001$; retweets: $t(1613) = 24.24$, $p < .0001$), which supports *H4a*. However, we found no differences in engagement between tweets about negative ingroup and outgroup events (favorites: $t(1613) = 1.16$, $p = .25$; retweets: $t(1613) = 1.28$, $p = .20$), which means that *H4b* is not supported.

4. Discussion and conclusion

In the current project, we focused on intergroup dynamics in social-media commentaries of sports games on Twitter, by contrasting various types of bias in a naturalistic setting. Specifically, we looked at biases in communication volume, balance, fairness, and recipient engagement on Twitter. Traditionally, these types of biases have been studied separately in controlled experiments (e.g., Beukeboom & Burgers, 2019; McLeod et al., 2017). By contrast, our study investigated these biases together in real-life social media data and demonstrates that focusing on Twitter commentaries of sports games can be a fruitful ways to explore these biases in real-life settings. Our results for the different bias types are uniform in that some intergroup processes are consistently reflected in social-media commentaries while others are not.

The first intergroup process on which we focused was ingroup favoritism, which was reflected in all analyses. In terms of tweet volume (*H1*), clubs placed more tweets during wins than during draws or losses. In terms of balance, a larger proportion of tweets focused on positive ingroup (vs. outgroup) events (*H2a*). In terms of fairness, a larger proportion of actually occurred positive ingroup (vs. outgroup) events were reported (*H3a)*. Thus, ingroup favoritism was reflected through biases in tweet volume, balance, and fairness. Fan behavior also reflects these tendencies, given that tweets featuring positive ingroup (vs. outgroup) events received more online engagement (*H4a*). Overall, social-media commentaries posted by clubs were biased by intergroup dynamics in line with SIT (Tajfel & Turner, 1986): clubs reported relatively more of their own positive events compared to those of their opponents, which was amplified by fans who engaged more with these tweets mentioning positive events of their own team compared to their opponents.

The second intergroup process that can be used to emphasize the positive distinctiveness of the own team is outgroup derogation (Tajfel & Turner, 1986). In our study, however, we found no evidence for outgroup derogation in live commentaries and their responses. After all, for balance, we found no differences in the proportion of tweets focusing on negative outgroup (vs. ingroup) events (*H2b*). Similarly, for fairness, the proportion of actual negative outgroup and ingroups events that were reported (*H3b*) did not differ from each other. This was also reflected in fan behavior, because we found no differences in online engagement for tweets mentioning negative ingroup (vs. outgroup) events (*H4b*).

[6] We found that the distributions of the dependent variables of (a) Proportion Tweets with Events, (b) Proportion Events Tweeted, and (c) Proportion Unique Events were skewed. To reduce the potential impact of outliers, we applied a log(1 + x) transformation to these dependent variables and recalculated the analyses of these dependent variables (see Online Appendix E at https://osf.io/c6wqy). These analyses lead to similar outcomes and conclusions.

The discrepancy between ingroup favoritism and outgroup derogation can be explained in several (related) ways. First, a key goal of social-media feeds for sports teams is engaging with their fan base (Price et al., 2013), and speakers who display a pattern of in-group favoritism are perceived as good group members (Assilaméhou & Testé, 2013). Thus, these positive events may be seen as most important, leading to more social-media focus by teams and fans. Second, our findings align with earlier research on sports communication (e.g., Arpan & Raney, 2003; Kim & Billings, 2017), which implied that media that report on negative events and ingroup losses may be evaluated more negatively by fans. Third, our results correspond to previous research that demonstrated that online conversations between ideologically like-minded groups are generally less negative than online conversations between ideologically opposed groups (Marchal, 2022). This could explain why the live commentaries did show a pattern of ingroup favoritism, but hardly focused on negative events or ingroup losses.

In our study, we found that the live commentaries both follow and deviate from intergroup biases as predicted by SIT (Tajfel & Turner, 1986). On the one hand, our study shows that online live commentaries follow intergroup dynamics as set out in SIT (Tajfel & Turner, 1986) in that they consistently demonstrate a biased pattern of in-group favoritism. These findings have important implications for the place of these live commentaries within the broader topic of sports reporting. Live Twitter commentaries are transmitted in one-way communication to the followers of a specific team (Cable & Mottershead, 2018), which resembles the one-way transmission of traditional sports reporting. Nevertheless, our analysis demonstrates that live Twitter commentaries have a different function than traditional sports journalism. The latter should strive to report on the game in a neutral way that does justice to the events that happened during the game and contain the various perspectives during the game. Live Twitter commentaries, by contrast, present the team's own perspective and serve mainly to engage with the team's own fans (Price et al., 2013). This means that they do not adhere to this philosophy of traditional sports reporting, but instead present a picture of the game that overreports the own team's positive events and underreports the opponent's positive events. Thus, this genre of Twitter commentaries should be seen and treated as distinct from traditional sports reporting.

On the other hand, we find that live Twitter commentaries deviate from intergroup dynamics as proposed by SIT (Tajfel & Turner, 1986) when focusing on negative events. That is, we find that the live commentaries contain relatively few references to negative events, regardless of whether these negative events can be attributed to the ingroup or the outgroup. As such, the live commentaries do not seem to contribute much to social-media polarization that focuses on attacking outgroup members (Van Bavel et al., 2021). Other studies have also demonstrated that outgroup derogation may be framed in subtle ways. For instance, research on linguistic bias has demonstrated that differences in the use of specific types of linguistic formulations (e.g., language abstraction, negations, irony) can serve to emphasize intergroup differences (for an overview of linguistic-bias research, see Beukeboom & Burgers, 2019). Future research could look at the potential use of linguistic biases in these Twitter commentaries.

In addition, other research demonstrates that teams and athletes are frequently attacked and suffer abuse on social media in other settings (e.g., MacPherson & Kerr, 2021; Stamm & Boatwright, 2021). For instance, fans more often direct their negative responses and abuse to players' individual social-media handles than to the club as a whole (MacPherson & Kerr, 2021). In other cases, online fan groups may perpetuate an exclusionary rhetoric among themselves without directly addressing a club and/or player (Seijbel et al., 2022). This means that social media can be a toxic place for teams and athletes, and future research can shed more light on the circumstances under which social media can be constructive in fostering a sense of fan identity and team identification compared to the instances under which social media create a toxic and polarized fan climate. One way to do this would be to focus more on comments made: while we analyzed the number of favorites and retweets as indicators for online engagement, future research may also involve the content of comments on Twitter messages (e.g., when fans express schadenfreude at negative outgroup events).

In all, our study provides new insights in how sports clubs and fans engage with live commentaries, which have several theoretical and practical implications. First, our results support theoretical predictions from SIT (Tajfel & Turner, 1986) about ingroup favoritism, but not on outgroup derogation in live Twitter commentaries. In this way, our study provides additional support from a more naturalistic setting to confirm predictions from SIT which has been mainly investigated in experimental contexts (e.g., Assilaméhou & Testé, 2013; Burgers et al., 2015; Iacoviello & Spears, 2021). Given the importance of intergroup dynamics for online polarization (Marchal, 2022; Rathje et al., 2021; Van Bavel et al., 2021), these are important new insights. Second, our results demonstrate how live Twitter commentaries by sports clubs do not necessarily adhere to general journalistic norms on balance (Schaefer & Fordan, 2014; Zeldes et al., 2008) and fairness (Boudana, 2016). Thus, stakeholders who engage with these Twitter commentaries (e.g., fans, journalists) should be aware that this new online genre of live Twitter commentaries should be approached differently from traditional sports journalism (cf. Grimmer, 2017).

An important caveat of our study is that we focused on Dutch-language social-media handles from *Eredivisie* clubs. While this competition is the highest tier of soccer in the Netherlands, clubs from larger European leagues boast more followers from different countries. For instance, at the time of data collection, Ajax Amsterdam had 1.2 million followers, which was the highest number of all Dutch teams. By contrast, the follower count of Twitter feeds for popular European soccer teams like Real Madrid (36.6 million Spanish-language Twitter followers), Manchester United (25 million English-language Twitter followers) or Liverpool FC (16.9 million English-language Twitter followers) was considerably larger (Jahns, 2021). Furthermore, soccer fan cultures differ across European countries (Spaaij, 2007). Thus, it would be interesting to replicate our study with Twitter commentaries by soccer teams from a different country (see also Braun et al., 2021). In addition, fan cultures and perceptions of rival fans can also differ between individual sports (Havard et al., 2013). Thus, we also recommend to replicate our current study with social-media commentaries placed by teams from other sports (e.g., basketball, hockey).

To sum up, the current paper focuses on different types of bias across intergroup situations in real-life social-media data. Specifically, we focused on four types of intergroup bias: (1) biases in communication volume, (2) balance, (3) fairness, and (4) recipient engagement. To address this issue, we conducted an analysis of one season of live Twitter commentaries by Dutch *Eredivisie* clubs. For all four bias types, we found evidence of ingroup favoritism, but not of outgroup derogation. This study thus shows how social-media content in a sports context can be used to study intergroup dynamics in a naturalistic setting.

Credit author statement

Christian Burgers: Conceptualization, Methodology, Software, Formal analysis, Writing - Original Draft, Writing - Review & Editing, Supervision, Project administration. Camiel Beukeboom: Conceptualization, Methodology, Writing - Original Draft, Writing - Review & Editing. Pamela A. L. Smith: Conceptualization, Methodology, Formal analysis, Writing - Original Draft, Writing - Review & Editing. Tammie van Biemen: Formal analysis, Writing - Original Draft, Writing - Review & Editing.

Data availability

Data and code are available from the Open Science Framework (OSF) at https://osf.io/c6wqy/

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2022.107528.

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