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Engagement performance of rage bait content: An analysis of fan accounts' derby-week posts on X

Öfke tuzağı içeriklerinin etkileşim performansı: X'te taraftar hesaplarının derbi haftası paylaşımları üzerine bir analiz

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Abstract

Examining the use of rage bait in derby week posts by football fan accounts on X platform, this study analyzes the relationship between these contents and interaction performance. To contribute to the limited literature on how rage bait operates in fan communication, quantitative content analysis was used in the research. A total of 204 posts shared between April 20-30, 2026, from ultrAslan (Galatasaray) and 12 Numara (Fenerbahçe) accounts were coded based on posting period, media type, content topic, content function, usage, rage bait type, and interaction indicators. The findings reveal that rage bait is more frequently observed in ultrAslan posts and are more often associated with mockery, asserting superiority, and belittling the opponent after a victory. In 12 Numara posts, where rage bait is predominantly constructed through narratives of injustice, scandal, and accusation, rage bait content is observed before and during the match, while after the match, this content gives way to discussions about internal club crises. In the general sample, posts containing rage bait generated higher retweet, like, and total engagement rates. Account-based analyses revealed that rage bait were associated with a higher retweet rate on ultrAslan and a higher comment rate on 12 Numara. Revealing that rage bait is not merely a single engagement-boosting tactic, this study concludes that it operates as a situational platform practice shaped by account identity and match context.

Keywords: Rage bait, fan accounts, X, social media engagement, digital fan culture

Öz

X'te futbol taraftar hesaplarının derbi haftası paylaşımlarında öfke tuzağı kullanımının incelendiği bu çalışmada söz konusu içeriklerin etkileşim performansıyla ilişkisi analiz edilmektedir. Taraftar iletişiminde öfke tuzağının nasıl işlediğine ilişkin sınırlı literatüre katkı sunmak amacıyla araştırmada nicel içerik analizi yöntemi kullanılmıştır. 20–30 Nisan 2026 tarihleri arasında ultrAslan (Galatasaray) ve 12 Numara (Fenerbahçe) hesaplarından paylaşılan toplam 204 gönderi; paylaşım dönemi, medya türü, içerik konusu, içerik işlevi, öfke tuzağı kullanımı, öfke tuzağı türü ve etkileşim göstergeleri çerçevesinde kodlanmıştır. Bulgular, öfke tuzağının ultrAslan paylaşımlarında daha sık görüldüğünü ve galibiyet sonrasında daha çok alay, üstünlük kurma ve rakibi küçümseme diliyle ilişkilendiğini ortaya koymaktadır. Öfke tuzağının ağırlıklı olarak haksızlık, skandal ve suçlama anlatılarıyla kurulduğu 12 Numara paylaşımlarında ise maç öncesi ve sırasında öfke tuzağı içerikleri görülürken bu içerikler maç sonrasında yerini kulüp içi kriz gündemine bırakmıştır. Genel örneklemde öfke tuzağı içeren paylaşımlar daha yüksek retweet, beğeni ve toplam etkileşim oranları üretmiştir. Hesap bazlı analizler, öfke tuzağının ultrAslan'da daha yüksek retweet oranıyla, 12 Numara'da ise daha yüksek yorum oranıyla ilişkili olduğunu açığa çıkarmaktadır. Öfke tuzağının tek tip bir etkileşim artırma taktiğinden ibaret olmadığını gözler önüne seren bu çalışma, hesap kimliği ve maç bağlamına göre şekillenen durumsal bir platform pratiği olarak işlediği sonucuna varmıştır.

Anahtar Kelimeler: *Öfke tuzağı, taraftar hesapları, X, sosyal medya etkileşimi, dijital taraftar kültürü*

Introduction

Having moved beyond their role as everyday spaces for accessing news and engaging in interpersonal communication, social media platforms also function as digital public arenas where cultural affiliations, collective emotions, rivalries, and identity performances become visible. Particularly on platforms like X, whose communicative architecture is shaped by rapid flows, immediate reactions, and heightened exposure, users take an active role in circulation through liking, commenting, reposting, and replying as much as they consume the content. It situates social media culture within a communicative field where emotions, conflicts, and group affiliations are continuously reproduced through platform logics.

In this environment, the circulation of a post depends on the kinds of responses it can elicit, not simply on its publication. Some forms of content are designed less to inform or entertain than to prompt users to respond, object, share, or take part in a discussion. Oxford University Press's selection of rage bait as its Word of the Year for 2025 underlines how this reaction-oriented content form has gained salience within digital culture. Rage bait refers to a form of online content that seeks to generate traffic or engagement by provoking anger, outrage, or an impulse to respond among users (Oxford University Press, 2025).

Which cannot be reduced to crude or aggressive content, rage bait's defining feature lies in its ability to generate engagement by activating the user's anger, objection, mockery, identity-based sensitivities, or impulse to give a response. It also differs from explicit engagement baits that directly ask users to like, comment on, or share a post (Oxford University Press, 2025; Silverman & Huang, 2017). The circulation of social media content may be driven by reaction and conflict as much as by attention or participation.

Football fandom provides a particularly fruitful example for examining this issue. Beyond the practice of following sporting competitions, fandom constitutes a form of cultural identity woven through belonging, rivalry, antagonism, and collective emotion (Sandvoss, 2005; Wann & Branscombe, 1993). Doing more than convey match information, scores, and club-related updates, fan accounts motivate fan communities, target rival identities, organise perceptions of injustice, and circulate discourses of superiority and mockery following victory, in social media environments. Fan accounts can be read as significant digital actors that is located at the intersection of social media culture and fan culture.

Existing research addresses social media engagement through platform logic, algorithmic visibility, emotional diffusion, participatory culture, and fan identification (Berger & Milkman, 2012; Jenkins, 2006; Klinger & Svensson, 2015; Van Dijck & Poell, 2013; Wann & Branscombe, 1993). However, how rage bait content is discursively constructed in fan accounts and which forms of engagement it is associated with have not yet been sufficiently clarified. Moreover, the relationship between rage bait and engagement should not be treated as linear. A post may generate more likes, more reposts, or more comments, yet these behaviours do not carry the same communicative meaning. Likewise, victorious and defeated sides should not be expected to produce the same repertoires of rage in the aftermath of the same derby. While mockery, superiority, and the belittling of the rival may become more visible on the victorious side, narratives of injustice, scandal, accusation, and crisis may be more prominent on the defeated side.

This study examines the content production practices of football fan accounts on X during derby week in relation to rage bait use and engagement dynamics. In Turkish football culture, major clubs are commonly associated with well-known supporter groups that function as recognisable fan communities beyond institutional club communication. Within the Galatasaray–Fenerbahçe rivalry, ultrAslan and 12 Numara are treated as the principal supporter communities publicly identified with Galatasaray and Fenerbahçe, respectively. The study analyses the official public X accounts of these two supporter communities to provide a

bounded comparison of opposing fan positions in the Galatasaray–Fenerbahçe derby setting. 204 posts which are shared by these two accounts between 20 and 30 April 2026 have been analysed with the method of quantitative content analysis. It has been aimed in this study to contribute to the literature by examining rage bait performance both in the overall sample and within each account's engagement structure.

Platform Logic, Networked Publics, and Engagement-Based Visibility

Social media platforms are not neutral channels through which content is merely disseminated. They are platformised communication environments that operate through the interrelated dynamics of visibility, spreadability, engagement, and algorithmic selection. On platforms like X, whether a piece of content enters public circulation is shaped mostly by how it is presented and which forms of user response it is capable of eliciting. Boyd's (2010) concept of networked publics emphasises that social media environments differ from conventional spaces of public communication through affordances such as persistence, replicability, scalability, and searchability.

Within platform environments, visibility is closely tied to user engagement. According to Van Dijck and Poell (2013), social media logic operates through the principles of programmability, popularity, connectivity, and datafication. Indicators of likes, comments, reposts, and views should be read as platform metrics that signal the circulatory potential of content rather than as merely technical measurements. Similarly, it has been argued by Klinger and Svensson (2015) that network media logic differentiates content production and distribution from the dynamics of traditional media logic. It is necessary to examine the content production of fan accounts on X in terms of both content forms and engagement performance.

Social media systems translate user actions into datafied signals and use these signals to organise attention. As Gillespie (2014) argued, algorithms are socio-technical mechanisms involved in selecting what becomes publicly relevant. Bucher (2012) has also explained how algorithmic systems can produce a "threat of invisibility" that encourages users and content producers to adapt their practices to platform logics. Gerlitz and Helmond (2013) have conceptualized likes and social buttons as part of a "like economy" in which seemingly simple user actions become data flows and value-producing signals. It seems that engagement metrics are not external indicators added after communication takes place. Actually, they help to understand the conditions under which social media communication is produced, evaluated, and circulated.

Emotional Diffusion, Anger, and Out-Group Targeting

On social media platforms, the circulation of content is linked to its informational value. However it appears to the emotional responses it arouses among users are being more detective. Berger and Milkman (2012) identify emotional arousal as one of the key factors influencing the diffusion of online content, arguing that high-arousal emotions such as anger and anxiety may encourage users to share content more readily. In a similar vein, Brady et al. (2017), have demonstrated that moral-emotional language can strengthen the circulation of content across social networks.

In fan account communication, references to referees, video assistant referee (VAR) decisions, football federations, rival teams, rival supporters, scandal, or injustice can turn sporting rivalry into a field of moral judgement, grievance, and group-based reaction. Rathje et al. (2021) further report that out-group hostility can increase social media engagement, a finding especially relevant to football fandom, where rivals often mark the symbolic boundaries of group identity.

The role of anger becomes clearer when emotional diffusion is understood as both a psychological response and a socially reinforced platform process. Papacharissi's (2014) concept of affective publics suggests that digital publics are organised through affective flows in which users narrate,

share, and amplify collective feelings alongside rational deliberation. Brady et al. (2021) have argued that moral outrage expression can be amplified through social learning, as users may reproduce forms of outrage that receive positive social feedback in online environments. From this perspective, rage bait operates as a platform-oriented affective trigger that may convert anger, grievance, and group-based sensitivity into measurable engagement.

Fandom, Belonging, and Digital Fan Communities

Participatory culture, which emphasises fans' active role in interpreting, reproducing, sharing, and circulating media content (Jenkins, 2006), and the sports fan identification literature, which links team attachment to group belonging and collective identity (Sandvoss, 2005; Wann & Branscombe, 1993), show that sports fandom, as a social relation constructed through collective identity, belonging, symbols, rituals, and opposition, extends beyond following a team's performance. Accordingly, football fan accounts, which are not merely pages that transmit match updates, should be regarded as digital actors that reproduce fan identity and organise collective emotions.

The sociology of sport have framed fandom as a cultural field where rituals, collective memory, symbolic boundaries, commercial structures, and emotional attachments intersect. Delaney and Madigan (2015) emphasise that sport functions as a social institution embedded in culture, identity, media, economy, and everyday life, rather than as a purely competitive activity. In the Turkish football setting, Bora, Reiter, and Horak (1993 / 2020) have approached football as a popular cultural universe which is shaped by teams, supporter subcultures, commercialisation, and collective meanings. Bora (2001) has brought together discussions that illuminate the social, political, and cultural textures of Turkish football. Ünsal's (2005) analysis of anger and violence in commercialising Turkish football and Toklucu's (2001) account of supporter culture further underline how fandom in Türkiye is intertwined with tribune culture, affective attachment, rivalry, and collective mobilisation.

Rival teams and rival supporters are also central elements of identity formation in sports fandom. Fan identity is often constructed through the question of "against whom are we defined?" as much as through "who are we?". Sanderson's (2013) study has indicated that fans may use online environments to manage social identity threats, redraw group boundaries, and devalue out-group members. It clarifies why belonging, rivalry, and mobilisation need to be considered together in analyses of fan accounts.

Türkiye-based research also offers some important national frame for examining football fandom, social media, and supporter identity. For instance, Oyman and Başbozkurt (2021) have linked Turkish football fans' social identities and team identification to their social media motivations and behaviours. As an another example, Çelik (2022) has identified news and information, fandom, promotion, interaction, and entertainment among the motives that lead Turkish fans to follow their teams on social media. More directly in relation to supporter groups and derby-related digital culture, Olca and Özdemir (2023) have described social media as one of the key environments in which fan culture is represented, and Arslan (2025) documents meme-based forms of digital humour, rivalry, and collective emotion after Süper Lig derbies on X. These studies establish the digital and interactional background of Turkish football fandom. On the other hand, rage bait as a specific content function and its relationship with engagement performance in derby-week fan account communication remains insufficiently examined.

Rage Bait, Engagement Bait, and Provocative Discourse

Clickbait, engagement bait, and rage bait differ according to the forms of user behaviour they aim to elicit. While clickbait targets clicks through curiosity and information gaps, engagement bait invites explicit forms of participation such as likes, shares,

or comments. Rage bait, aims to provoke reactive participation through anger, objection, outrage, and the impulse to give response. Blom and Hansen (2015) have defined clickbait through forward-reference and incomplete information structures. Scott (2021) has explained it through curiosity gaps and relevance expectations. Rage bait differs because circulation is generated through conflict, objection, mockery, and argument.

Engagement bait refers to content that artificially encourages users to like, share, or comment (Silverman & Huang, 2017). Rage bait, by contrast, may push users to reply, object, mock, or debate even without a direct participation request. Shin, DeFelice, and Kim (2025) distinguish rage bait from information bait in social media news headlines and report that rage-bait headlines are associated with higher engagement. However, existing work has focused mainly on news headlines or general digital content, leaving fan communication, where group affiliation and rivalry are intense, underexplored.

Online incivility, outrage discourse, and framing help clarify the forms rage bait may take. Coe, Kenski, and Rains (2014) link uncivil expression to changes in discussion environments, Berry and Sobieraj (2016) associate mockery and affective intensification with attention and attachment, and Semetko and Valkenburg's (2000) conflict and responsibility frames help explain narratives of injustice, scandal, blame, and accusation. Based on this literature, the study codes rage bait through three subtypes: provocation through anger / threat, insult / mockery, and exposé / scandal / accusation.

Method

Research Design and Methodological Framework

This study used quantitative content analysis to examine rage bait use and engagement dynamics in derby-week posts shared by the ultrAslan and 12 Numara accounts between 20 and 30 April 2026. Content analysis allows communication materials to be classified through predefined categories and recurring patterns to be compared systematically (Krippendorff, 2004 / 2019). Accordingly, instead of constructing a causal model, it focused on comparatively identifying the content production and engagement patterns of two fan accounts during derby week. Guided by this research design, the study seeks to answer the following research questions:

RQ1: How is the derby-week content production of the ultrAslan and 12 Numara accounts distributed in terms of posting period, media type, content topic, and content function?

RQ2: How does the use of rage bait differ between the two fan accounts and across the pre-match, match-day, and post-match periods?

RQ3: Through which discursive forms do different types of rage bait emerge in the ultrAslan and 12 Numara accounts?

RQ4: Do posts containing rage bait differ from those without rage bait in terms of raw engagement and view-adjusted engagement rates?

RQ5: When the internal dynamics of each account are taken into consideration, does the engagement performance of rage bait content operate in the same way, or does it manifest through different forms of engagement?

Case Selection, Data Source, and Scope

The data source consisted of publicly accessible X posts shared during derby week by ultrAslan and 12 Numara. These accounts were selected because Turkish football fandom commonly associates major clubs with highly visible supporter communities alongside institutional club accounts. ultrAslan is widely associated with Galatasaray supporters, while 12 Numara is widely associated with Fenerbahçe supporters. The study focused on their official public X accounts because they provide a direct site for observing supporter-driven communication, rivalry, emotional mobilisation, and derby-week interaction. The selection criterion was not follower size or prior engagement ranking, but the accounts' status as principal supporter-community accounts identified with opposing sides of the Galatasaray-Fenerbahçe derby,

their public accessibility, their activity during the selected period, and their relevance to fan communication. Other fan pages, informal supporter accounts, and smaller supporter groups were excluded because the study was designed as a bounded two-case comparison rather than a mapping of the broader Galatasaray and Fenerbahçe fan-account ecology.

The dataset covered posts published between 20 and 30 April 2026. Each individual X post was the unit of analysis. The final sample included 204 posts: 59 from ultrAslan and 145 from 12 Numara. Posts were grouped as pre-match, match-day, and post-match so that the language of anticipation, match-day provocation, and post-match repertoires of victory, defeat, crisis, or mobilisation could be compared.

Coding Framework and Variables

The coding scheme was developed by drawing explicitly on the literature reviewed above and by adapting these conceptual discussions to the structure of the dataset. Categories concerning platform visibility, media forms, and engagement indicators were informed by work on networked publics and social media logic (Boyd, 2010; Klinger & Svensson, 2015; Van Dijck & Poell, 2013). Categories related to fandom, belonging, rivalry, and mobilisation drew on fan and sports-fandom literature (Jenkins, 2006; Sanderson, 2013; Sandvoss, 2005; Wann & Branscombe, 1993) as well as Türkiye-based studies on social media and football fandom (Arslan, 2025; Çelik, 2022; Olca & Özdemir, 2023; Oyman & Başbozkurt, 2021). The rage bait variable and its subtypes were informed by the literature on emotional diffusion and out-group targeting (Berger & Milkman, 2012; Brady et al., 2017; Rathje et al., 2021), engagement bait and rage bait (Oxford University Press, 2025; Shin et al., 2025; Silverman & Huang, 2017), and online incivility, outrage discourse, and framing (Berry & Sobieraj, 2016; Coe et al., 2014; Semetko & Valkenburg, 2000). Rather than being drawn from a pre-existing scale, the coding framework was therefore constructed by combining these conceptual distinctions with the specific communicative structure of the football derby context. For each post, descriptive information was first recorded. This included the post number, date, day, account, posting period, text, and URL.

Content was coded for media type (text only; text + image; text + video; text + quoted image / video; image only; video only; mixed), content topic (match / score / performance; fans / stands / stadium; football players; technical staff / head coach; club management / president / transfers; rival team / rival supporters; referee / VAR / TFF; general information / commemoration / special day / announcement), and content function (news / information / announcement; engagement prompt / question / poll; entertainment / humour / irony; celebration / congratulation / achievement reporting; support / belonging / motivation / mobilisation; criticism / reaction / disappointment; awareness / demand / call; provocation / rage bait; commemoration / condolence / special day).

Rage bait presence was coded dichotomously. A post was not coded as rage bait merely because it used a negative or critical tone; the decisive criterion was whether it was likely to activate anger, objection, mockery, accusation, defence, sharing, or discussion. Posts coded as rage bait were assigned to one of three subtypes: anger / threat, insult / mockery, or exposé / scandal / accusation. Engagement performance was measured through comments, retweets, likes, and views. Total engagement equalled comments + retweets + likes; comment, retweet, like, and total engagement rates were calculated by dividing each indicator by views.

Data Collection Process and the Fixing of Engagement Indicators

Publicly accessible X posts from both accounts were reviewed for the selected period, and each post's content characteristics, engagement indicators, and URL were recorded. Because social media metrics change over time, comments, retweets, likes, and views were fixed according to the final

check on 5 May 2026. Posts published earlier had more time to accumulate engagement; therefore, raw values were interpreted together with view-adjusted rates, without treating those rates as eliminating time effects completely.

Data Analysis

Descriptive statistics were used to report the distribution of accounts, posting periods, media types, topics, functions, rage bait use, and rage bait types. Pearson's chi-square test assessed the relationship between account and rage bait use. Mann-Whitney U tests compared posts with and without rage bait because engagement data were skewed and group sizes were unequal. The analysis proceeded in three stages: overall-sample comparisons, general account-level engagement comparisons, and within-account comparisons. Raw engagement indicators were reported through medians to reduce the influence of extreme values.

Ethics, Reliability, and Limitations

This non-interventional content analysis used only publicly accessible X posts and visible engagement indicators from the ultrAslan and 12 Numara accounts. It did not involve direct contact with human participants, private accounts, user comments, individual profiles, or personal information; therefore, no ethics committee application was made. Coding was conducted by a single researcher, so no inter-coder reliability test was applied. To strengthen consistency, all posts were coded according to the same decision rules, and the dataset was reviewed after coding. The study is limited to two official public supporter-community accounts and a single Galatasaray-Fenerbahçe derby week. Other fan pages and smaller supporter groups were outside its bounded two-case design. The findings should not be generalized to all Galatasaray or Fenerbahçe supporter accounts, all Turkish football fan accounts, or other derby settings. Engagement indicators were recorded on a fixed date, but posts had unequal time to accumulate engagement; user comments and algorithmic mechanisms were also not analysed.

Findings

Content Structure and Raw Engagement Profile by Account

A total of 204 posts shared by the official public X accounts of ultrAslan and 12 Numara between 20 and 30 April 2026 were analysed. Of these posts, 59 (28.9%) belonged to ultrAslan and 145 (71.1%) to 12 Numara. As shown in Table 1, content was published most intensively on match day and during the post-match period. While ultrAslan's posts were concentrated more heavily on match day, post-match posts accounted for a relatively larger share of 12 Numara's content. This distribution guides to a temporal difference in the content production rhythm of the two accounts during derby week.

Table 1. Distribution of content by account and posting period

Account	Pre-match n (%)	Match day n (%)	Post-match n (%)	Total n (%)
ultrAslan	13 (22.0)	26 (44.1)	20 (33.9)	59 (28.9)
12 Numara	25 (17.2)	58 (40.0)	62 (42.8)	145 (71.1)
Total	38 (18.6)	84 (41.2)	82 (40.2)	204 (100.0)

It has been presented in Table 2 that the distributions of the accounts by media type, content topic, and content function. In terms of media type, text + image posts stood out in both accounts, although 12 Numara used video and quoted image / video formats more frequently than ultrAslan. With regard to content topic, match / score / performance-oriented posts appeared at similar rates in both accounts; however, fans / stands / stadium and rival team / rival supporters were more prominent in ultrAslan's content, whereas club management / president / transfers were markedly more visible in 12 Numara's posts.

When content functions were examined, news / information / announcement emerged as the dominant function in 12 Numara's posting structure,

while support / belonging / motivation / mobilisation and provocation / rage bait were more visible in ultrAslan's content. This differentiation suggests that ultrAslan adopted a more affective and mobilising communication practice during derby week, whereas 12 Numara displayed a stronger orientation toward agenda-setting and the monitoring of internal club debates.

Table 2. Distribution of media type, content topic, and content function by account

Variable	Category	ultrAslan n (%)	12 Numara n (%)	Total n (%)
Media type	Text only	9 (15.3)	27 (18.6)	36 (17.6)
	Text + image	42 (71.2)	59 (40.7)	101 (49.5)
	Text + video	6 (10.2)	38 (26.2)	44 (21.6)
	Text + quoted image / video	2 (3.4)	18 (12.4)	20 (9.8)
	Image only	0 (0.0)	2 (1.4)	2 (1.0)
	Video only	0 (0.0)	1 (0.7)	1 (0.5)
Content topic	Match / score / performance	17 (28.8)	42 (29.0)	59 (28.9)
	Fans / stands / stadium	15 (25.4)	7 (4.8)	22 (10.8)
	Content about football players	4 (6.8)	14 (9.7)	18 (8.8)
	Technical staff / head coach	1 (1.7)	12 (8.3)	13 (6.4)
	Club management / president / transfers	0 (0.0)	53 (36.6)	53 (26.0)
	Rival team / rival supporters	10 (16.9)	6 (4.1)	16 (7.8)
	Referee / VAR / TFF	5 (8.5)	9 (6.2)	14 (6.9)
	General information / commemoration / special day / announcement	7 (11.9)	2 (1.4)	9 (4.4)
Content function	News / information / announcement	17 (28.8)	97 (66.9)	114 (55.9)
	Engagement prompt / question / poll	0 (0.0)	11 (7.6)	11 (5.4)
	Entertainment / humour / irony	2 (3.4)	0 (0.0)	2 (1.0)
	Celebration / congratulation / achievement reporting	5 (8.5)	2 (1.4)	7 (3.4)
	Support / belonging / motivation / mobilisation	15 (25.4)	5 (3.4)	20 (9.8)
	Criticism / reaction / disappointment	0 (0.0)	11 (7.6)	11 (5.4)
	Awareness / demand / call	1 (1.7)	5 (3.4)	6 (2.9)
	Provocation / rage bait	15 (25.4)	13 (9.0)	28 (13.7)
	Commemoration / condolence / special day	4 (6.8)	1 (0.7)	5 (2.5)

Note: Percentages represent column percentages calculated within each account's total number of posts.

Median raw view counts and median total engagement values by media type are presented in Table 3. Although the highest median total engagement value for ultrAslan was observed in the text + quoted image / video category, this finding should be interpreted cautiously, as the category contained only two posts. Among categories with greater representational strength, text + image and text + video posts stood out with relatively high raw engagement levels. In 12 Numara's content, text-only posts likewise produced comparatively lower engagement medians, whereas formats incorporating visual or video elements generated higher values.

These findings suggest that the use of multimodal formats may be associated with higher raw engagement levels in both accounts. Nevertheless, differences observed across media types should be assessed together with content topic, posting period, and the accounts' broader engagement structures.

Table 3. Median raw view counts and total engagement by account and media type

Account	Media type	n	Median views	Median total engagement
ultrAslan	Text + quoted image / video	2	640450	43233.50
	Text + image	42	116750	15137.50
	Text + video	6	120050	14769.50
	Text only	9	106900	9287
12 Numara	Image only	2	154850	4664.50
	Text + quoted image / video	18	98950	1138
	Text + image	59	93800	1055
	Text + video	38	76300	1038.50
	Text only	27	56200	397

Note: Media types with n=0 and n=1 were excluded from the table. Categories with n=2 should be interpreted cautiously. Raw total engagement consists of the sum of comments, retweets, and likes.

Median raw view counts and median total engagement values by content topic are presented in Table 4.

Table 4. Median raw view counts and total engagement by account and content topic

Account	Content topic	n	Median views	Me ga
ultrAslan	Rival team / rival supporters	10	369100	51
	Referee / VAR / TFF	5	342400	41
	Content about football players	4	117050	26
	Fans / stands / stadium	15	116400	14
	General information / commemoration / special day / announcement	7	102100	86
	Match / score / performance	17	78500	63
12 Numara	Referee / VAR / TFF	9	219900	38
	Rival team / rival supporters	6	331000	23
	Technical staff / head coach	12	100500	20
	Fans / stands / stadium	7	117900	17
	General information / commemoration / special day / announcement	2	43100	13
	Content about football players	14	103200	10
	Club management / president / transfers	53	77500	78
	Match / score / performance	42	54750	44

Note: Categories with n=0 and n=1 were excluded from the table. Categories with n=2 should be interpreted cautiously. Raw total engagement consists of the sum of comments, retweets, and likes.

In ultrAslan's content, rival team / rival supporters and referee / VAR / TFF posts stood out with higher median total engagement values, whereas in 12 Numara's content the referee / VAR / TFF category was particularly prominent. Match / score / performance content appeared frequently but produced lower medians. The pattern suggests that topics linked to rivalry, fairness, and grievance carried stronger engagement potential than content volume alone.

rage bait content more robustly, the following analyses examine view-adjusted engagement rates and statistical comparisons.

Use of Rage Bait, Temporal Patterns, and Engagement Performance

The distribution of rage bait use by account is presented in Table 6. The findings show that rage bait content was used at a higher rate by ultrAslan than by 12 Numara.

Table 5. Median raw engagement values by account and content function

ultrAslan						
Content function	**n**	**Comments**	**Retweets**	**Likes**	**Views**	**Total engagement**
Provocation / rage bait	15	201	2000	42000	342400	44143
Celebration / congratulation / achievement reporting	5	35	819	25000	117100	25770
Entertainment / humour / irony	2	23	586.5	17500	98750	18109.5
Support / belonging / motivation / mobilisation	15	58	615	14000	96700	14908
Commemoration / condolence / special day	4	35.5	464.5	7500	107000	7992.5
News / information / announcement	17	43	192	6000	86300	6319
12 Numara						
Content function	**n**	**Comments**	**Retweets**	**Likes**	**Views**	**Total engagement**
Provocation / rage bait	13	423	147	2000	299000	2684
Criticism / reaction / disappointment	11	173	336	2000	153000	2520
Awareness / demand / call	5	68	145	2000	76400	2213
Celebration / congratulation / achievement reporting	2	116.5	187	1766	85800	2069.5
Support / belonging / motivation / mobilisation	5	98	106	1000	117900	1204
Engagement prompt / question / poll	11	181	33	404	141400	774
News / information / announcement	97	64	19	479	56500	569

Note: Categories are ordered from highest to lowest within each account according to median total engagement. Total engagement consists of the sum of comments, retweets, and likes; views are not included in total engagement. Given the skewed distribution of engagement metrics, median values are reported instead of means.

Table 5 presents median raw engagement values by content function. In both accounts, content classified under provocation / rage bait ranked among the highest categories in terms of median total engagement. In ultrAslan's content, this category was followed by celebration / congratulation / achievement reporting and support / belonging / motivation / mobilisation, whereas in 12 Numara's posts, criticism / reaction / disappointment and awareness / demand / call stood out.

This descriptive pattern indicates that the repertoires of highly engaging content in the two accounts rested on different affective foundations. While the content that stood out in ultrAslan's posts was shaped around victory, belonging, and the provocation of rivals, the content that attracted stronger engagement in 12 Numara's posts was more closely associated with reaction, disappointment, and crisis narratives. Nevertheless, in order to assess the engagement performance of

This difference was also statistically significant, $\chi^2(1, N = 204) = 9.593$, $p = .002$. In terms of rage bait types, the two accounts diverged markedly: provocation through insult / mockery was more dominant in ultrAslan's posts, whereas provocation through exposé / scandal / accusation was more prominent in 12 Numara's content. This distribution indicates that provocative content was constructed through different discursive strategies in the two accounts.

Table 6. Rage bait use and rage bait types by account

Variable	**Category**	**ultrAslan n (%)**	**12 Numara n (%)**	**Total n (%)**
Rage bait present?	No	44 (74.6)	132 (91.0)	176 (86.3)
	Yes	15 (25.4)	13 (9.0)	28 (13.7)
Rage bait type	Provocation through anger / threat	3 (20.0)	2 (15.4)	5 (17.9)
	Provocation through insult / mockery	8 (53.3)	1 (7.7)	9 (32.1)
	Provocation through exposé / scandal / accusation	4 (26.7)	10 (76.9)	14 (50.0)

Note: For the variable "rage bait present?", percentages were calculated on the basis of each account's total number of posts. For the variable "rage bait type", percentages were calculated only among posts coded as rage bait.

The distribution of rage bait use across posting periods is shown in Table 7. In the overall sample, rage bait content appeared most intensively on match day. However, the temporal pattern was not the same for the two accounts. In ultrAslan's posts, rage bait increased on match day and continued into the post-match period. In 12 Numara's content, by contrast, rage bait was confined to the pre-match and match-day periods, with no such content observed after the match. This finding suggests that the match outcome affected the production of provocative discourse in the two fan accounts in different ways.

Table 7. Rage bait use by account and posting period

Account	Pre-match n/rage bait n (%)	Match day n/rage bait n (%)	Post-match n/rage bait n (%)	Total n/rage bait n (%)
ultrAslan	13/ 2 (15.4)	26/8 (30.8)	20/5 (25.0)	59/15 (25.4)
12 Numara	25/3 (12.0)	58/10(17.2)	62/0 (0.0)	145/13 (9.0)
Total	38/5 (13.2)	84/18 (21.4)	82/5 (6.1)	204/28 (13.7)

Note: Percentages were calculated on the basis of the total number of posts within each account and posting period. For example, ultrAslan's match-day rage bait rate was calculated based on 8 rage bait posts among the 26 posts it published on match day.

The raw engagement indicators of posts containing and not containing rage bait are compared in Table 8. Median values show that posts coded as rage bait had higher levels of comments, retweets, likes, views, and total engagement. This descriptive difference leads to a notable raw engagement and reach advantage for rage bait content. Because posts differed in their reach, however, engagement performance was not assessed solely through raw counts; in the subsequent analyses, view-adjusted rates were used.

Table 8. Median raw engagement indicators by rage bait status

Engagement indicator	No rage bait n	No rage bait Median	Rage bait n	Rage bait Median
Number of comments	176	63	28	333
Number of retweets	176	50.5	28	1000
Number of likes	176	1000	28	18500
Number of views	176	86400	28	325350
Total engagement	176	1129	28	20206.5

Note: Since engagement indicators displayed skewed distributions and some posts received exceptionally high engagement, median values are reported instead of means. Total engagement consists of the sum of comments, retweets, and likes; views are not included in total engagement.

Table 9 compares the engagement rates of posts containing and not containing rage bait. Rage bait content performed significantly better in terms of retweet rate, like rate, and total engagement rate, whereas the difference in comment rate was not statistically significant.

Table 9. Comparison of engagement rates by rage bait status

Engagement indicator	No rage bait Median (%)	Rage bait Median (%)	Mean Rank No	Mean Rank Yes	Mann–Whitney U	Z	p
Comment rate	0.08	0.1	99.66	120.32	1965	-1.72	.085
Retweet rate	0.06	0.35	95.48	146.61	1229	-4.256	< .001
Like rate	1.16	5.97	98.18	129.64	1704	-2.619	.009
Total engagement rate	1.43	6.34	97.46	134.18	1577	-3.057	.002

Note: Rates were calculated by dividing the relevant engagement indicator by the number of views and are presented as percentages. The p value displayed as .000 in the SPSS output is reported as < .001 in the table.

These overall-sample differences also need to be read against the possibility that the two accounts already had distinct engagement dynamics. The general engagement rates of ultrAslan and 12 Numara were therefore compared independently of the rage bait variable.

Table 10. Comparison of general engagement rates by account

Engagement indicator	ultrAslan Mean Rank	12 Numara Mean Rank	Mann–Whitney U	Z	p
Comment rate	70.02	115.72	2361	-5.013	< .001
Retweet rate	166.83	76.32	482	-9.928	< .001
Like rate	173.05	73.79	115	-10.888	< .001
Total engagement rate	173.02	73.81	117	-10.883	< .001

Note: The Mann–Whitney U test was applied to examine general differences in engagement rates between the two accounts. The p values displayed as .000 in the SPSS output are reported as < .001 in the table.

As Table 10 reports, the two accounts differed significantly across all engagement rates. While 12 Numara stood out in terms of comment rate, ultrAslan ranked higher in retweet rate, like rate, and

total engagement rate. This result underlines the need to consider the broader engagement cultures of the accounts when interpreting the effects of rage bait content.

Table 11 presents the within-account comparisons. In ultrAslan, rage bait created a significant difference only in retweet rate; in 12 Numara, only in comment rate. Rage bait therefore activated resharing and circulation for ultrAslan, but replying, objection, and discussion for 12 Numara.

Table 11. Within-account comparison of engagement rates by rage bait status

Account	Engagement indicator	Mean Rank No	Mean Rank Yes	Mann–Whitney U	Z	p
ultrAslan	Comment rate	27.61	37	225	-1.828	.068
	Retweet rate	24.93	44.87	107	-3.882	< .001
	Like rate	28.07	35.67	245	-1.48	.139
	Total engagement rate	27.8	36.47	233	-1.689	.091
12 Numara	Comment rate	70.26	100.85	496	-2.505	.012
	Retweet rate	70.95	93.77	588	-1.869	.062
	Like rate	73.23	70.69	828	-0.208	.836
	Total engagement rate	72.35	79.62	772	-0.595	.552

Note: The Mann–Whitney U test was applied separately for each account. "No" refers to posts not containing rage bait, whereas "Yes" refers to posts containing rage bait. The p value displayed as .000 in the SPSS output is reported as < .001 in the table.

Taken together, the findings indicate that rage bait content was associated with engagement performance, although this relationship varied according to both account and type of engagement. While rage bait content performed better on certain engagement rates in the overall sample, within-account analyses showed that this effect emerged primarily through retweets in ultrAslan's posts and through comments in 12 Numara's posts. The influence of rage bait content should therefore be interpreted in light of the broader engagement structures of the accounts and their discursive positioning within the derby context.

Discussion and Conclusion

This study examined the use of rage bait in football fan accounts' derby-week posts on X and its relationship with the engagement performance of such content. The findings showed that rage bait differed between the two fan accounts not only in terms of frequency of use, but also in the discursive forms through which it was constructed. While rage bait appeared more frequently in ultrAslan's posts and was associated with a repertoire of mockery, superiority, and the belittling of the rival in the context of victory, it remained more limited in 12 Numara's content and, following the match, gave way to an agenda centred on internal club crisis, management, and the head coach. Taken together, this pattern indicates that rage bait should be understood not as a fixed and unidirectional engagement-boosting tactic, but as a context-dependent communication practice shaped by match outcome, fan position, account identity, and the shifting agenda of the period.

At the level of the overall sample, posts containing rage bait had higher raw reach and engagement values and differed significantly from posts without rage bait in terms of retweet rate, like rate, and total engagement rate. This result is consistent with the literature suggesting that high-arousal emotions can strengthen the circulation of online content (Berger & Milkman, 2012; Brady et al., 2017; Shin et al., 2025). Yet the non-significant difference in comment rate indicates that rage bait does not necessarily generate direct discussion or responses in every case. The relationship between rage bait and engagement should thus be assessed through the question of which forms of engagement it activates under which conditions, rather than through the linear proposition that "rage bait generates more engagement."

Account-based analyses provide one of the most explanatory findings of the study in this regard. While posts containing rage bait produced a statistically significant difference only in retweet rate within the ultrAslan account, they stood out only in terms of comment rate within the 12 Numara account. This divergence is also consistent with the broader engagement structures of the two accounts: ultrAslan ranked higher in retweet rate, like rate, and total engagement rate, whereas 12 Numara was more prominent in comment rate. The effect of rage bait should therefore

be interpreted within each account's own engagement culture. In ultrAslan's posts, rage bait was more closely associated with the recirculation of content and the expansion of collective visibility, whereas in 12 Numara's content, it more strongly activated behaviours such as commenting, objecting, and joining the discussion.

The discursive basis of this differentiation is equally clear. In ultrAslan's posts, rage bait was concentrated primarily in the category of provocation through insult / mockery, whereas in 12 Numara's content, provocation through exposé / scandal / accusation was more prominent. This distinction suggests that victorious and defeated fan positions construct rage bait through different rhetorical forms. The language of mockery, belittlement, and superiority in ultrAslan's content may be read as a practice of establishing symbolic dominance over the rival and reinforcing in-group belonging in the aftermath of victory. By contrast, 12 Numara's narratives of injustice, scandal, operation, and accusation may be interpreted as attempts to manage the identity-based and affective tension produced by defeat, to externalise the reasons for loss, and to create a shared ground of reaction within the fan community. This discursive divergence also overlaps with the observed engagement patterns: the victorious side's shareable narrative of superiority appears to feed retweet rates more strongly, whereas the defeated side's narratives of objection and victimhood appear to stimulate comment rates more directly.

The temporal findings further indicate that match outcome constitutes an important threshold transforming the communication practices of fan accounts. Rage bait content was most heavily concentrated on match day across the overall sample; however, the two accounts diverged in the post-match period. While rage bait discourse continued in ultrAslan's posts after the match, no content coded as rage bait was observed in 12 Numara's post-match output. This does not mean that anger disappeared entirely from the defeated fan account; rather, it suggests that anger shifted direction. The outward-oriented provocative discourse constructed around rivals, referees, and injustice narratives before and during the match was transformed after defeat into an inward-oriented agenda of crisis definition and management criticism. Considered alongside Papacharissi's (2014) notion of affective publics, this finding demonstrates that fan accounts develop different discursive and engagement strategies in response to changing emotional atmospheres throughout derby week.

The findings also show that the engagement performance of fan accounts cannot be explained solely through the rage bait variable. Content function, media type, and content topic were also influential in shaping levels of visibility and engagement. Although the provocation / rage bait function occupied a notable position in terms of raw total engagement in both accounts, celebration, support, and mobilisation content in ultrAslan's posts, as well as criticism, reaction, and disappointment content in 12 Numara's posts, also generated high engagement. Similarly, multimodal formats and themes concerning rival teams / rival supporters and referees / VAR / TFF emerged among the content clusters associated with heightened engagement. Understanding social media engagement therefore requires attention not only to aggregate counts of likes, comments, or retweets, but also to which types of content resonate, within which account identities, under which emotional conditions, and through which forms of engagement.

The study has limitations. It focuses on the official public X accounts of two principal supporter communities associated with the Galatasaray-Fenerbahçe derby and on one derby week; other fan pages, informal supporter accounts, and smaller groups were excluded. The findings should not be generalized to all Galatasaray or Fenerbahçe supporter accounts or to all football fan communication in Türkiye. Engagement indicators were fixed on one date, although posts had different exposure times. The study also does not analyse user comments or the technical operation of algorithmic visibility. Future research may compare multiple derbies, accounts, and longer periods, and may examine comments, quoted posts,

reply chains, and circulation networks to trace how rage bait spreads within fan communities.

Declarations

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Conflicts of Interest: The author declares no conflicts of interest related to this study.

Ethical Approval: Ethical committee approval was not required for this study because This study constitutes a non-interventional content analysis conducted on publicly accessible X posts. No direct contact was established with human participants, no data were collected from users, and no content from private or closed accounts was analysed.

Data Availability: The data that support the findings of this study are available from the corresponding author upon reasonable request.

AI Disclosure: *ChatGPT was used for The scholarly content of this work—including the research questions, theoretical framework, methodology, analyses, and conclusions—was entirely produced by the author. During the preparation of the study, OpenAI ChatGPT was used to a limited extent for preliminary source exploration, consultation on which analyses would be appropriate, and the review of the English translation. All sources identified through ChatGPT were examined by the researcher, and only those deemed appropriate were selected and cited by the researcher. AI-based tools were strictly not used in this study for data collection, data generation, statistical analysis, or citation / reference generation. All data analyses were conducted by the researcher personally using SPSS. The author reviewed, edited, and verified all AI-assisted outputs and takes full responsibility for the content of the manuscript.*

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