Twitter interaction between audiences and influencers. Sentiment, polarity, and communicative behaviour analysis methodology

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Abstract

Twitter is one of several social networks with the highest numbers of users in Spain. In spite of this, how are communicative relationships developed in the digital environment among influencers who have emerged on the Internet? These personalities have a stronger influence on children and young people than traditional celebrities. The aim of this work is to study the communicative interaction generated on the profiles of Spanish influencers with the most followers on *Twitter*, based on the number of content items generated and the responses they receive from users. The polarity and sentiment conveyed by these communications have also been analysed. By processing publications in real time using machine learning based on sentiment analysis, 48,878 tweets and retweets from five influencers were studied over a period of 40 days. The results show that the publications reached nearly 200 million followers, and despite being fourth in terms of the number of followers, @IbaiLlanos is the influencer who leads the conversations on *Twitter* with the highest number of tweets, retweets, and audience share. Among the most popular topics, sporting events stand out. This study has also confirmed that the most frequently stated emotion is surprise, and that positive messages prevail over those that are negative and neutral with regard to polarity. Nevertheless, the linear regression data has verified that the main trend is toward publishing negative messages, with a lower statistical correlation, which is a behaviour that might possibly be duplicated on other social networks.

Keywords

Twitter; Audiences; Influencers; Sentiment analysis; Parasocial interaction; Polarity; Emotions; Communication; Social networks; Social media; Hashtags; Theoretical advance; Methodology.

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1. Introduction

One of the main activities carried out by users on social networks continues to be the following of influencers. According to data provided by *IAB Spain* (2022), 53% of internet users follow this type of account. In fact, 22% of those who have a profile on *Twitter* engage in this activity. Moreover, it is one of the most widely used social networks, trailing only behind *Instagram*, *YouTube*, *Facebook* and *TikTok*, mainly among individuals aged 12-17 (78%).

Twitter has become an important tool for sharing opinion and information among its members (**Ali** *et al.*, 2020). Moreover, this channel gives a voice to celebrities whose tweets become news, along with more intimate, personal information than other intermediaries can provide (**Bond**, 2016; **Kowalczyk**; **Pounders**, 2016). In addition, it is fundamental for trending, virality of content, and the development of online dialogue (**Jain**; **Sinha**, 2020). From the follower's perspective, **Stever** and **Lawson** (2013) differentiate between the big fans who perceive *Twitter* as a direct connection to their favourite celebrity and, on the other hand, the less intense followers who see this channel as a diversion related to something or someone else who they like.

Measurements of these relationships have been analysed from different approaches, although **Riquelme** and **González-Cantergiani** (2016) report that the most frequent are associated with tracking users and the responses posted by them, as well as the content creators themselves. This paper examines the *Twitter* accounts of the Spanish influencers who have the largest followings among teenagers and young adults based on sentiment analysis, a technique developed in recent years and reported in the related literature (**Sailunaz**; **Alhajj**, 2019; **Chang**, 2019; **Lahuerta-Otero**; **Cordero-Gutiérrez**, 2016; **Bae**; **Lee**, 2012, among others).

The study of emotion on social networks allows for an in-depth understanding of the attitudes and feelings of their users (**Arce-García**; **Orviz-Martínez**; **Cuervo-Carabel**, 2020). This research has taken a new approach by analysing the behaviour generated by main Spanish influencers and trying to gain a deeper understanding of the emotional discourse therein and the resulting polarisation. Along these lines, the topics that interest the followers of these influencers have been examined, based on an analysis of the most frequently appearing hashtags, the purpose of which is to classify the thematic content.

Through sentiment analysis, this study is especially relevant due to its contribution to understanding the emotions expressed by users, as well as the topics that arouse the most interest. Moreover, it goes one step further in providing an overview of the trends observed through the parametric technique of linear regression, which helps to predict behaviour patterns.

2. State of the issue

2.1. Activity and behaviour of influencers. Strategies to achieve popularity in social networks

Numerous research studies related to communication and marketing have attempted to describe the characteristics of an influencer, a key player in the daily use that teenagers make of social networks (**Lou**; **Kim**, 2019). In the comparison between this figure and celebrities offered by **Gräve** (2017), we find one of the defining features of influencers: their effectiveness on social networks and, consequently, the fact that they are considered part of the community.

Starting from this point, the classification of micro influencers and macro influencers established by **Berne-Manero** and **Marzo-Navarro** (2020), among others, has been set forth, with the latter being defined as those with more than 100,000 followers who are perceived as professionals, and whose content is more trustworthy. For their part, the micro influencers have a number of followers in the range of 1,000-50,000, whom followers find to be more approachable and friendly. The status of the figures in our study is even higher, as they are defined by **Lowe-Calverley** and **Grieve** (2021), and **Zarei** *et al.* (2020), among others, as mega-influencers, having more than one million followers.

In this relationship with users, **Santamaría-de-la-Piedra** and **Meana-Peón** (2017) conclude that influencers tend to be respectful of the opinions and comments raised by their audience, although **Fernández-Muñoz** and **García-Guardia** (2016) note that having a larger number of followers is not linked to a higher level of interactivity. **Campbell** and **Farrel** (2020) provide some characteristics of the influencers focused on marketing that may be adaptable to the sentiment analysis addressed in this research: their specialization in determined topics, a large number of coincidences with their followers that results in similar interests with them, and their tendency to generate a close bond with their viewers derived from a continuous communication.

On the other hand, **Loria** *et al.* (2020) offer two novel, additional characteristics regarding influencers in video games: their influence on followers is consolidated over time, and they are strategically positioned, generally speaking. This is combined with the gradual creation of communication codes that foster an increase in followers by empathising with their way of expressing themselves (*Autocontrol*, 2020). Regarding the generated empathy, **Kim**, **Kim** and **Collins** (2021) recommend that influencers should post self-disclosures that are more personal and emotional rather than professional and descriptive, as the former have a more positive effect on followers and lead to greater engagement.

In the specific case of *Twitter*, **Alp** and **Öğüdücü** (2018) identify them according to the speed of reaction (time elapsed between the publication of a tweet until it receives a retweet), the number of topics they deal with, level of activity (number of active days and average number of daily tweets), and finally, authenticity, which is focused on the degree of originality of the content they publish. Based on these assumptions, the authors observe that the most high-impact influencers are characterised by faster reaction times. Moreover, they focus on fewer topics, yet post a large number of tweets that are mostly original. Regarding this last point, **Kowalczyk** and **Pounders** (2016) agree that the authenticity shown by influencers on *Twitter* is positively associated with a larger following among users. However, this unique aspect of comments is also related to popularity on other social networks such as *Instagram* (**Casaló**; **Flavián**; **Ibáñez-Sánchez**, 2020).

> As one of the most influential social networks in today's world, *Twitter* allows content to be viralised, creates trends and drives online conversions

Along the same lines, **Lahuerta-Otero** and **Cordero-Gutiérrez** (2016) have found that influencers use a small number of words (but more hashtags), they follow a large number of users, and they state their opinions clearly. **Mueller** and **Stumme** (2017) make the further comment that content which is more familiar to followers leads to greater recognition, and they also state that the popularity of a person on *Twitter* is associated with the number of tweets posted. However, other studies (**Wallner**; **Krigslein**; **Drachen**, 2019; **Jain**; **Sinha**, 2020) clarify that popularity is not connected to the number of retweets, which is in line with the concept of authenticity mentioned above, although these authors point out that the most influential figures receive many Likes. For that reason, research by authors such as **Edelmann** (2017) or **Bossen** and **Kottasz** (2020), concludes that users are more inclined to click on Like rather than post replies or comments.

2.2. Parasocial interaction and sentiment analysis

The parasocial phenomena of interaction and relationships share a common origin, as they were first proposed by **Horton** and **Wohl** (1956) and later developed in the academic literature. In order to differentiate between the two concepts, the study by **Dibble**, **Hartmann** and **Rosaen** (2015) is essential. Based on previous work, these authors propose interaction as a false sense of relationship that only occurs during viewing, while a true parasocial relationship occurs over the long term, even though it starts with interaction.

From the perspective of our analysis, the closest parasocial phenomenon is considered to be that of interaction. In effect, it is a matter of observing the reactions of users to certain content. This study has not included whether this impact lasts longer than the viewing itself, nor how it affects the routines and decision-making of users. While it is true that many of those who use content published by the influencers analysed in this research are likely to be regular followers, we cannot assume that the interactivity generated by this content involves a parasocial relationship.

From this point on, **Stever** and **Lawson** (2013) have shown that sharing one's own personal tastes has an impact on such interaction. However, authors such as **Krause**, **North** and **Heritage** (2018) and **Hwang** and **Zhang** (2018) clarify that the user's interest in this type of relationship comes from an attempt to compensate for their own lack of personality and low self-esteem, which is much more acute among adolescents and young people.

With regard to the choice of channels used to establish contact, **Bond** (2016) has found a generally stronger impact of this phenomenon on *Twitter* than on other networks, although teenagers prefer to follow their favourite characters on *Instagram* and *Facebook*. Nevertheless, a positive attitude from influencers, which includes posts of engaging and interactive content, is linked to a stronger desire among users to imitate the figures they follow (**Ki**; **Kim**, 2019). In a comparative study by **Kreissl**, **Possler** and **Klimmt** (2021) between *let's* players and conventional celebrities, the authors discovered that parasocial interaction is similar in both cases, yet in the case of the former, it is based more on interactivity generated rather than idolatry toward the figure. Along the same lines, **Khajeheian** and **Kolli** (2020) note that the representation on *Twitter* of a certain game (*Pokemon Go*) encouraged conversation between users and players. When re-tweeting by fans is added to the mix, the main consequence is the reinforcement of parasocial interaction with the heightened perception that users identify influential figures with their friends in real life (**Kim**; **Song**, 2016). In addition to other fields, this concept is used in marketing for the promotion of certain brands by influencers (**Jiménez-Castillo**; **Sánchez-Fernández**, 2019).

The relationships between followers and influencers has also been addressed in the academic literature through sentiment analysis. Indeed, sentiment analysis was defined by **Liu** (2017) as the computational study of moods, affection, and emotion. **Sánchez-Rada** and **Iglesias** (2019) have added user reaction to this metric. Therefore, if one bears in mind that the bond of parasocial interaction is characterized by the different degrees of affection and emotion aroused, in our case by the content of an influencer, its measurement through sentiment analysis is considered pertinent and appropriate.

In this regard, **Chang** (2019) proposes a model of influence based on sentiment generated. He notes that more posts on topics related to everyday life result in more support from followers, while controversial posts that cause conflict result in an emotional reaction from users, yet they also lead to a higher number of negative comments.

Using a similar approach, **Sailunaz** and **Alhajj** (2019) have shown that the emotional sign perceived in a tweet (positive or negative) mostly generates the same sentiment in followers' comments, a result that coincides with those previously found by **Berger** and **Milkman** (2012), **Bae** and **Lee** (2012) and by **Drescher** *et al.* (2018), in relation to their research on the publication of content on *Twitter* referring to the video game Destiny. Finally, the perspective based on lexical discourse analysis applied by **Ishtiaq** (2015) is noteworthy as well. This author notes that on this social network, nouns often show a neutral sign that can be modified by adjectives, while verbs are the greatest intensifiers of sentiment polarity and are usually reinforced by adverbs.

The application of sentiment analysis enables the in-depth study of the opinions that Internet users express through the content they share on social networks, and consequently, the parasocial interaction generated. Studying polarity and emotion provides knowledge about their opinions, which can influence the perspective and decision making of other users (**Cho**, 2018). Thanks to its amplification, sentiment analysis explores the polarity of posts, which can be positive, negative, or neutral, as well as the feelings involved, which can be surprise, happiness, anger, sadness, fear, dislike, or neutral (**Hernández-Ruiz**; **Gutiérrez**, 2021; **Nemes**; **Kiss**, 2021; **Vizcaíno-Verdú**; **Aguaded**, 2020). In addition to applying Human Language Technology (HLT), upon which sentiment analysis is founded, the present study links its findings to quantitative techniques through the statistical study of the linear regression model that has allowed us to examine the behavioural patterns of users.

3. Objectives

The interaction of adolescents and young people is mediated by digital technology and social networks (**Nesi**; **Choukas-Bradley**; **Prinstein**, 2018; **Anderson**; **Jiang**, 2018; **Suárez-Álvarez**; **García-Jiménez**, 2021). As such, the aim of this paper is to gain knowledge regarding the communicational interaction generated by *Twitter* postings in relation to the most widely followed influencers in Spain. Such interaction has been analysed through opinion mining, machine learning, and sentiment analysis, which has allowed us to study the opinions, polarity, and emotion generated by users on social networks (**Cardoso** *et al.*, 2019, **Vizcaíno-Verdú**; **Aguaded**, 2020). The magnitude of the postings has also been studied, which includes the volume of tweets and retweets, the audience, which shows the impact of the communications, and the number of Likes. We have also investigated the content by studying the most frequently repeated topics labelled with hashtags, as well as the polarity and emotion of the underlying sentiments of *Twitter* comments.

The questions addressed by this research are the following:

Q1. What is the volume of posts generated on *Twitter* in relation to the influencers with the most followers?

Q2. What is the audience with regard to the conversations that are monitored on *Twitter*?

Q3. Which influencer receives the most Likes?

Q4. What are the most recurrent topics determined by the hashtags addressed in the postings?

Q5. What is the predominant polarity and emotion in the publications?

Q6. Are behaviour patterns predicted in the polarity of posted messages?

4. Methodology

A quantitative methodology has been applied through machine learning, opinion mining, and sentiment analysis using natural language processing (machine learning) (**Dridi**; **Recupero**, 2019). The research is organised in two stages. The first focuses on the selection of influencers for the time period studied, and the second phase is directed at the analysis of tweets and retweets, hashtags, and sentiment.

The sample selection criteria have been established based on the fact that the sample units (influencers) are known for their activity on social networks, and not for other professional reasons, and they have more than 1 million followers on their *Twitter* account, which makes them mega-influencers on this social network (**Fernández-Prados** *et al.*, 2021; **Lowe-Calverley**; **Grieve**, 2021; **Zarei** *et al.*, 2020).

To identify them, we have consulted the VII Study on *Facebook*, *Twitter*, *Instagram*, and *LinkedIn* users in Spain (2021), carried out by the consultancy firm known as *Social Media Family*, which analyses personal and professional *Twitter* accounts according to the number of followers, whether their profiles are active and verified (with daily or monthly access to the platform), and their professions. Following the sample selection, the research focuses on accounts and organisations that have emerged from social networks as gamers, streamers, or any other profession that has appeared in the digital environment. To confirm the number of followers, as well as their importance, we have used the socialblade.com tool, which has allowed us to categorise influencers by using filters in order to confirm their importance. As shown in Table 1, the results display the influencers, the identified profession, and the number of followers registered on the last day of the research, which shows oscillations due to their continuous activity. The selected time period was 40 days, from 23 May to 3 July 2021.

Table 1. Influencers

Accounts	Profession	Number of followers (in million)
@Rubiu5	Gamer	16.8
@vegetta777	Gamer	7.9
@mangelrogel	Gamer	6.8
@IbaiLlanos	Streamer	4.6
@bysTaXx	Gamer	4.2

In the second stage of the research, we worked with the *GPLSI Social Analytics* application of the *University of Alicante* which, through *Twitter* APIs and Human Language Technology (HLT), identifies and extracts mentions and facts that appear in different types of texts (**Hernández-Ruiz**; **Gutiérrez**, 2021).
https://socialanalytics.gplsi.es

> Influencers are recognized for their efficiency on social networks, and adolescents view them as key players in their daily use of social networks

In conformance with the definition of analysis application, semantic enrichment has been carried out on the basis of open, connected data for opinion mining and the detection of sentiment analysis. In this way, the polarity of expressed opinions (positive, negative, and neutral) is obtained by means of natural language processing, text analysis, and computational linguistics in order to systematically extract, quantify, and study emotional status and subjective information.

There has been no discrimination of any words or expressions in order to obtain a complete, in-depth analysis of the publications made during the time frame studied.

The results have been analysed using the *Real Statistics Resource Pack*, which offers greater potential for statistical analysis. Tukey's Honestly Significant Difference post-hoc test (HSD) has been applied in order to compare the means of the levels of a factor after rejecting the null hypothesis, and the Anova test of variance has also been performed, which compares variances between means through the integrated study of social and behavioural science data (**Judd**; **McClelland**; **Ryan**, 2017).

This has been supplemented with the exploitation of data using the statistical modelling technique of linear regression ($Y = \beta 0 + \beta iX + \varepsilon i$), through the analysis of a response variable in relation to the independent variables (**Court**; **Williams**, 2011), in order to understand and predict the behaviour of the followers of the profiles analysed, which confirms that the closer the correlation value is to 1, the stronger the relationship.

4.1. Coding of variables

In order to study the variables, we reviewed the works of **Hasan** *et al.*, (2018), and **Sailunaz** and **Alhajj** (2019), who have examined sentiment and emotion on *Twitter* through opinion mining, as well as **Nemes** and **Kiss** (2021), who have analysed sentiment and polarity on *Twitter* in relation to COVID-19. The study has also been complemented with work by **Berger** and **Milkman** (2012), who investigated the way in which emotion increases the virality of content, and **Vizcaíno-Verdú** and **Aguaded** (2020), who have examined the sentiment of children's accounts on *Instagram*. Measurements developed by the *GPLSI Social Analytics* platform have been used as well.

In analysing the magnitude of the postings, the following parameters have also been considered:

- The number of publications, calculated by summing the tweets and retweets in which influencers are mentioned.
- The number of authors, defined as the social network users who have mentioned one of the influencers' accounts in their postings with at least one tweet or retweet.
- The audience, considered to be the total number of followers of the authors who have named one of the influencers on *Twitter*.
- Ranking by number of likes.

In terms of content, the following aspects have been examined:

- The hashtags that are most widely used by authors that mention the influencers.
- The polarity classification of posts with sub-variables (positive, negative, and neutral), which has been performed by looking at the measurements analysed by the platform, as well as by considering the work of **Ahmad** and **Aftab** (2017) and **Gopi** *et al*., (2020) in their research on *Twitter* polarity.
- The feelings of anger, surprise, happiness, sadness, fear, dislike, and neutrality, which the selected organisations generate in their conversations on this social network, have been studied according to the classification offered by the sentiment analysis platform.

5. Results

A total of 48,848 publications (tweets + retweets) corresponding to the monitoring period from 23/05/2021 to 3/07/2021 have been tracked using the tool that analyses and makes predictions about the state of social opinion.

5.1. Magnitude of the publications on *Twitter*

Even though @IbaiLlanos is the second influencer with the fewest followers (4.6 million), it can be observed that he is the one who leads in the number of publications on *Twitter* with 46,122 tweets and retweets, followed by @ Rubius5 with 1,682 publications (tweets and retweets). The rest do not exceed 500 posts. As for the number of authors who mention the influencers analysed in their publications, 26,059 comment on @IbaiLlanos, and 1,066 mention @Rubius5 (Table 2).

Table 2. Volume of publications

Account	Tweets + retweets	Authors	Audience
@IbaiLlanos	46,122	26,059	175,598,411
@Rubius5	1,162	1,066	14,132,438
@vegetta777	375	242	7,542,822
@mangelrogel	356	252	2,161,129
@bysTaXx	343	212	1,158,697

> Professionalization of content is associated with the credibility, consolidation, and strategic positioning of social media influencers

The audience of the five accounts studied reached nearly 200 million (199,917,388), of which 175,598,411 belonged to @IbaiLlanos, 14,132,438 to @Rubius5, and 7,542,822 to @vegetta777. The evolution of the audience reveals that during the period of time studied, three high peaks were observed in the case of the influencer with the most followers (@IbaiLlanos), which corresponded to the following days: 23-05-2021, 06-06-2021, and 16-06-2021. On 23 May, the tweets focused mainly on the announcement of the so-called "Evening of the year", among others. This event was a boxing match organised on 26 May on the *Twitch* platform by @IbaiLlanos, in which six influencers (Future and Torete; Viruzz and Jagger; and Reven and ElMillor) entered the ring while @IbaiLlanos broadcast the match live. The event reached more than 1.5 million people, who were connected simultaneously, and it became the most widely viewed sporting event in *Twitch* history (**Ariza-Martín**, 2021; *Interactivadigital.com*, 2021). On 6 June, the posts were about the results their followers would receive from their university admissions tests, the *NBA* basketball game between the *Los Angeles Clippers* and *Dallas Mavericks*, and to a lesser extent, the boxing match between Floyd Mayweather and Logan Paul. On 16 June 2021, @IbaiLlanos' streaming presentation of the new song "Turreo" by Argentinian *cumbia* singer Elian Ángel Valenzuela (artistically known as L-Gante), was predominant, among other topics.

It is noteworthy that in the ranking related to number of Likes, @bysTaXx is the one who has the most with 569, of which 210 Likes are from 24-06-2021, and 199 are from the day after (25-06-2021), which coincides with the resumption of his streams with a game of *Counter-Strike: Global Offensive* on *Twitch*, after he returned from holiday. He is followed by @Rubius5 with 103 Likes, @IbaiLlanos with 87, @mangelrogel with 44, and @vegetta777 with 21. This coding indicates that although @IbaiLlanos has the most tweets and retweets with the largest audience, his followers are more likely to participate actively rather than exhibit passive behaviour limited only to viewing and clicking on Like.

5.2. Content analysis of the *Twitter* publications

5.2.1. Most frequently-used hashtags

The most frequent-used hashtags show that the content published is mainly focused on sporting events. Among the top twenty are included #laveladelaño, #laveladadeibiai, and #laveladadeiano with a total of 584 mentions. These tweets correspond to the publications resulting from the "Evening of the year" broadcast by @IbaiLlanos on his *Twitch* channel. In second place, #portaventura received 410 mentions in relation to the broadcast of *America's Cup* (#copaamerica; #copaamerica2021, which gained 137 mentions), carried out by @IbaiLlanos on his *Twitch* channel from *PortAventura World*, with the collaboration of footballers and sports commentators. Moreover, he has organised other previous events for *America's Cup* at the same amusement park. The next most common topics are focused on sports as well (#euro2020, #elcorazóndelaliga, #thehearttoflaliga, and #tokyo2020) with 126 hashtags in total.

Other issues are also addressed, such as #evau2021 and #gustazoconcedido, the latter of which is oriented toward an advertisement by the company *Grefusa* (@grefusa) within the framework of the #gustoConcedido campaign in which the company asks its followers to answer the following question through *Twitter*: "What is your greatest pleasure?" Within this marketing strategy, one highlight that stands out is the interview of @IbaiLlanos with the impersonator @raulperez_76, who clones the streamer by holding a conversation between the two of them on the *Twitch* platform, which had more than 110,000 views on *Twitter* on12-11-2021.

5.3. Polarity and emotion

Polarity analysis allows us to study whether tweets and retweets are positive, negative, or neutral. Of the 48,878 posts analysed, nearly half are positive (44.6%), while a smaller proportion are negative (31.5%), and neutral (23.9%).

According to each influencer, 57.1% of the posts by @vegetta777 were positive, 34.1% of those published by @bysTaXx were negative, and 34% of the posts by @mangelrogel were neutral. @IbaiLlanos and @Rubius5 received mostly positive messages, with 44.3% and 48.5%, respectively (Table 3).

Table 3. Polarity in the messages analysed

Twitter	Positive	Total %	Negative	Total %	Neutral	Total %	Total
@Rubius5	815	48.5	420	25.0	447	26.6	1,682
@vegetta777	214	57.1	59	15.7	102	27.2	375
@mangelrogel	178	50.0	57	16.0	121	34.0	356
@bysTaXx	138	40.2	117	34.1	88	25.7	343
@IbaiLlanos	20,452	44.3	14,763	32.0	10,907	23.6	46,122
Total	21,797	44.6	15,416	31.5	11,665	23.9	48,878

With regard to emotion, of the total number of 48,878 publications analysed, 4,088 posts showed the expression of some type of emotion (8.4% of the total). Surprise was the most predominant emotion, which appeared in 34.2% of all messages in which emotions were shown, followed by fear at 28.4%, and anger at 13.7%. The analysis reveals that surprise is the predominant emotion in posts referring to @IbaiLlanos, @bysTaXx, @mangelrogel, and @Rubius5. In the case of @vegetta777, happiness and fear are the most common emotions.

This study indicates a relationship of dependency between polarity and emotion. According to the values of η^2, the size of the effect between the variables is moderate in the case of polarity. However, in the case of sentiment, this effect ranges from moderate (the highest value for sadness stood at 0.535) to mild (the lowest value for dislike was 0.034) (Table 4).

Table 4. Means of polarity and sentiment identified, and the Anova test

	@Rubius5	@vegetta777	@mangelrogel	@bysTaXx	@IbaiLlanos	Anova 1 factor
Positive	48.45%	57.07%	50.00%	40.23%	44.34%	F = 41.0 p = .000 η^2 = .457
Negative	24.97%	15.73%	16.01%	34.11%	32.01%	F = 43.3 p = .000 η^2 = .470
Neutral	26.58%	27.20%	33.99%	25.66%	23.65%	F = 45.7 p = .000 η^2 = .484
Anger	0.95%	0.27%	0.56%	1.46%	1.16%	F = 29.9 p = .000 η^2 = .380
Surprise	2.32%	0.80%	4.49%	2.62%	2.89%	F = 12.1 p = .000 η^2 = .199
Happiness	1.07%	1.07%	2.53%	0.29%	0.36%	F = 22.4 p = .000 η^2 = .315
Sadness	1.66%	0.80%	0.84%	2.04%	1.12%	F = 53.1 p = .000 η^2 = .535
Fear	0.83%	1.07%	0.56%	0.00%	2.47%	F = 3.2 p = .024 η^2 = .061
Dislike	0.06%	0.53%	0.00%	0.29%	0.45%	F = 2.7 p = .046 η^2 = .034
Neutral	93.10%	95.47%	91.01%	93.29%	91.54%	F = 43.3 p = .000 η^2 = .471

A multiple comparison analysis (post-hoc test) was performed using Tukey's HSD test to establish comparisons and delve into existing differences between the variables. Once the existence of differences between the means is determined, the post-hoc rank test makes it possible to determine which means differ, and to identify the homogeneous subsets of the means. With regard to polarity, it has been observed that there are significant differences (p = 0%) between @IbaiLlanos and the rest of the influencers, which is not the case for the others (Table 5).

Table 5. Tukey's HSD post-hoc test. Polarity

Account 1	Account 2	Positive			Negative			Neutral		
		Lower	Upper	Sig.	Lower	Upper	Sig.	Lower	Upper	Sig.
@Rubius5	@vegetta777	-121,7	151,8	1,0	-87,6	105,7	1,0	-60,4	77,7	1,0
	@mangelrogel	-120,8	152,7	1,0	-87,6	105,7	1,0	-60,9	77,2	1,0
	@bysTaXx	-119,8	153,7	1,0	-89,1	104,2	1,0	-60,1	78,0	1,0
	@IbaiLlanos	354,2	627,7	0,0	261,9	455,2	0,0	192,5	330,5	0,0
@vegetta777	@mangelrogel	-135,9	137,7	1,0	-96,6	96,7	1,0	-68,6	69,5	1,0
	@bysTaXx	-134,9	138,7	1,0	-95,2	98,1	1,0	-68,7	69,4	1,0
	@IbaiLlanos	369,2	642,7	0,0	271,0	464,2	0,0	201,1	339,2	0,0
@mangelrogel	@bysTaXx	-135,8	137,8	1,0	-95,1	98,1	1,0	-68,2	69,9	1,0
	@IbaiLlanos	370,1	643,6	0,0	271,0	464,3	0,0	200,6	338,7	0,0
@bysTaXx	@IbaiLlanos	371,1	644,6	0,0	269,5	462,8	0,0	201,4	339,5	0,0

Significance level: 0.05

By applying the same test to the emotion encountered on *Twitter*, statistically significant differences (p = 0%) were found between @IbaiLlanos and the rest of the profiles, a finding that demonstrates that the publications that mention @IbaiLlanos show divergent behaviour in polarity and emotion with regard to the rest of the profiles analysed. The only exception observed is in the case of dislike, where no discrepancies were found. This result is consistent with the Anova analysis which, in relation to this sentiment, yields a value that is very close to the 0.05 significance level (p = 0.046).

5.3.1. Pattern of communicative behaviour according to polarity

In order to study the behavioural trend of *Twitter* posts that cite influencers, polarity (positive, negative, and neutral sub-variables) is related to the total number of posts by applying a simple linear regression model ($Y= \beta 0 + \beta 1X + \varepsilon$), which allows us to calculate the expected value of a variable. Polarity is used as the dependent response variable (Y), and the total number of publications is a function of the independent predictor variables (X), in order to test whether the volume of publications is linked to the polarity sub-variables (positive, negative, and neutral). $\beta 0$ and $\beta 1$ are the parameters of the regression coefficient model, and ε corresponds to the random error variable that explains the variability (Table 6).

Table 6. Regression model on the polarity sub-variables

	Negative	Neutral	Positive
Multiple correlation coefficient	0.97123258	0.89625709	0.96829123
Coefficient of determination R^2	0.94329272	0.80327677	0.93758791
Adjusted R^2	0.94180043	0.79809984	0.93594549
Standard error	85.6312442	114.293977	128.076516
Observations	40	40	40

All the sub-variables show regression coefficients (adjusted R^2) that are greater than 0, which indicates that with an increase in the number of publications, the number of tweets and retweets increases in all the polarity sub-variables, with the largest augmentation found in negative publications (adjusted R^2 = 0.94180043), and the smallest rise seen in neutral publications (adjusted R^2 = 0.80327677). Similarly, the multiple correlation coefficients in all three cases are greater than 0, which infers a direct relationship between the polarity sub-variables (positive, negative, and neutral) and the total number of publications. Therefore, it is the negative variable that shows the strongest correlation (correlation coefficient 0.97123258), which is evidence of the tendency to create and disseminate negative or disapproving content.

Along the same lines, the neutral sub-variable (correlation coefficient 0.89625709) shows the lowest correlation, which confirms the tendency among the authors toward more emotional behaviour based on the publication of comments that are more positive or negative rather than neutral.

6. Conclusions and discussion

This paper has analysed communicative relationships in the context of the parasocial interaction generated on the *Twitter* profiles of the Spanish influencers with the most followers. The study is based on the amount of content published and the number of responses received from users. Furthermore, the polarity and sentiment conveyed by this communication has been examined as well.

This research contributes to the theoretical advancement of social discourse and sentiment analysis on social networks in the field of social science. It reinforces the understanding of human behaviour, as well as the identification of behavioural patterns. As demonstrated in this study, such patterns tend to become emotional behaviour based on negativity, which can lead to similar conduct on other social networks, or even in the physical world. Moreover, the practical implications of our findings could be of use to the scientific community as well as to the professionals who work in influencer marketing.

The results will enable the understanding of attitudes and digital participation, as well as an increase in knowledge regarding the issues that matter most to internet users, which can be implemented in the corporate strategies of marketers. In addition, these findings will help marketing professionals to select influencers based not only on the number of followers they have, but also on the interactivity, emotionality, and polarisation they generate, bearing in mind the possible negative trends that may be arise in relation to the brands.

Contrary to the study by **Mueller** and **Stumme** (2017), the results of our research show that the account with the highest number of followers is not the one with the highest number of tweets and retweets, partly coinciding with the findings of **Fernández-Muñoz** and **García-Guardia** (2016) on the dissassociation between interactivity and number of followers. Nevertheless, the tendency of teenagers and young adults to click on Like instead of posting comments (**Edelmann**, 2017; **Bossen**; **Kottasz**, 2020) might explain our findings that retweets are not associated with more popularity, as suggested by **Wallner**, **Kirigslein** and **Drachen** (2019), and **Jain** and **Sinha** (2020)

It can also be observed that teenagers and young people (the main targets of the accounts studied) set clearly defined trends, as the activity generated by one of the influencers studied (@IbaiLlanos) is exponentially greater than the rest. In fact, he accounts for more than 87% of the audience registered in the five profiles. The number of retweets generated by Ibai Llanos also shows quick reaction time, a characteristic highlighted by **Alp** and **Öğüdücü** (2018) for increasing popularity on *Twitter*. It is also likely that this feature encourages a greater sense of belonging to the community, as described by **Gräve** (2017).

> Parasocial interaction gives rise to the heightened perception of users that they identify influencers as their friends in real life

In this regard, another significant aspect found in this study is that the influencer with the largest amount of content, @IbaiLlanos, receives a higher number of tweets and retweets, which indicates much more active participation by his followers than the engagement registered in other profiles, such as that of @bysTaXs. The followers of the latter account display more passive behaviour that is reflected in a high number of likes, but with far fewer text responses.

Content's polarity explains the popularity of the most followed influencers, who use it to attract a large number of followers by expressing their opinions

Sports, along with associated events, is the most recurring theme in the hashtags posted. Once again, the contributions of Ibai Llanos stand out from the rest. The most relevant event was a boxing match that Ibai Llanos broadcast himself. Moreover, the rest of the hashtags in this realm are mostly found on his account, as his online reputation is best known as a streamer. The professionalism that his content seems to symbolise can be associated with the credibility mentioned by **Berne-Manero** and **Marzo-Navarro** (2020), along with his gradual consolidation and strategic positioning on social networks (**Loria** *et al*., 2020).

The findings of this study have added a new strategy for achieving popularity. The appropriate selection of a topic is positively associated with greater recognition by social network users. In our research, it has been observed that content related to broadcasts and events involving sports arouses great interest among users, regardless of the author who publishes it.

It is also worth noting the brand-related hashtag, which was widely reproduced and backed by nearly 1.5 million likes. The advertising strategy that relies on these Internet influencers is relatively new, yet is being increasingly adopted. In this context, the code developed by *Autocontrol* (2020) states that the way in which the influencer uses language and communication allows them to increase their number of followers and, consequently, increase the audience's empathy with the brand that sponsors them (**Jiménez-Castillo**; **Sánchez-Fernández**, 2019). However, attention should be paid to this type of sponsorship because the interest shown by adolescents or young people toward this type of recommendation may be triggered by their attempt to seek an interconnection that compensates for their lack of self-esteem (**Krause**; **North**; **Heritage**, 2018; **Hwang**; **Zhang**, 2018).

In the analysis of reported sentiment, we found a high level of polarity, with a predominance of positive content (44.6%), followed by negative (31.5%), and lastly, by neutral content. However, the regression analysis has allowed us to observe a tendency toward negative messages, followed by those that are positive. In other words, the expected values show that the sign of the polarity will change, yet the polarity remains, with a tendency toward reducing neutral content. This result reinforces the findings of **Kim**, **Kim** and **Collins** (2021) who have observed that emotional content generates greater interest and attraction among followers.

In fact, the polarity of the content analysed in this study partly explains the popularity of the most widely followed influencers in Spain. Neutral comments, which are more descriptive than emotional, are the least used. The percentage of publications with some sign of polarity exceeds 88% in almost all the cases studied, with the exception of one influencer, @mangelroel, whose neutral content reaches more than one third (34%). We believe that these low registers are not a mere coincidence. Instead, we consider this to be a strategy of the figures under study, the purpose of which is to engage a larger number of followers by expressing their opinions (**Mueller**; **Stumme**, 2017). Similarly, the connection or relation between the user and the content, described in the concept of parasocial interaction (**Stever**; **Lawson**, 2013; **Dibble**; **Hartmann**; **Rosaen**, 2015; **Kim**; **Song**, 2016, among others), can lead to responses that mimic the influencer's comments (**Sailunaz**; **Alhajj**, 2019).

Finally, in the contents examined, it is worth highlighting the references made to other platforms, as well as to channels such as *Twitch*, which could be related to hypermediation, a concept developed mainly by **Scolari** (2008), among others, which is seen as a limitation of this study. Therefore, the authors suggest that this issue should be explored further in subsequent studies based on this theoretical approach, while taking into account the natural use of new technologies that currently characterises young people, adolescents, and children (**Yuste**, 2015). Another limitation of this study is the focus on Spanish influencers, who are mostly followed by users from Spain.

In this regard, it has been observed that recently emerging phenomena, an example of which is e-sports, attract young people to a large extent. The amount of interactivity generated by this type of competition, which has been detected in our analysis, provides evidence of this relationship. Moreover, these kinds of events are becoming increasingly international in scope. This should lead to an increase in the monitoring of other profiles that not only stand out for their textual comments, but also for their actions carried out at such events. These new practices of young people and minors give a broader, more diverse perspective to the already well-known globalisation of new technologies.

As such, other lines of research are recommended in which the globalisation mentioned is reflected in studies related to the activity of following influencers carried out by millennials and later generations. This, together with other issues, will pave the way for communication without language or linguistic limitations, which will at-

It has been observed that content related to broadcasts and events involving sports arouses great interest among users, regardless of the author who publishes it

tract the interest of these age groups toward international profiles. For future research, a comparison among countries is also proposed, since one of the limitations of this study is the fact that it is limited to Spanish influencers.

> Emotional content has a greater interest and attraction among followers

With regard to the limitations in the methodology applied, one aspect that stands out is the difficulty of the tool used in describing ambiguous words, which can be interpreted in different contexts (**Tauhid**; **Ruldeviyani**, 2020), or in providing a description of sarcastic expressions (**Bharti**; **Naidu**; **Babu**, 2017). This study has not been limited to keywords alone in the retrieval of content related to conversations generated in relation to influencers, yet the tweets were limited to those from Spain. Future research might evaluate the use of *Twitter* by the followers of the main influencers in other countries in order to understand their behaviour, feelings, and emotions. Furthermore, in line with **Garcia** and **Berton** (2021), the findings in this type of research are limited to *Twitter* users who are interested in influencers and interact with them as well.

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