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Measuring engagement on twitter using a composite index: An application to social media influencers

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ABSTRACT

Engagement on social networks is a complex concept, in which many interconnected, difficult-to-assess components interact. It is precisely this complexity which motivated this work, which proposes a composite index as a tool to measure engagement. Using TOPSIS, a multicriteria method that bases its ranking on minimizing the distance to the ideal point and maximizing the distance to the anti-ideal, a mix of indicators based on two approaches is used: the tweet approach and the follower approach. The former reflects engagement based on user production, and the latter measures engagement by popularity. This index was applied to a group of Social Media Influencers and a general ranking was obtained, as well as a ranking by each approach to measuring engagement. A comparison of the rankings generated by the different approaches shows the suitability and pertinence of both, as it is confirmed that they measure different aspects, and that both are needed to offer a holistic view of the engagement generated by a user on Twitter; this is a new finding compared to prior studies, which only focused on one approach or the other.

1. Introduction

Social networks have changed the way in which companies communicate with the public. The Web 2.0 or Social Web has meant that businesses are no longer the only ones who share information about products on a website; instead, users can also share and build trust in this information (Casaló, Flavián, Guinalíu & Ekinci, 2015; van Driel & Dumitrica, 2020; Zhang, Chintagunta & Kalwani, 2021). In fact, today, many decisions customers make are based on reviews for products or services that users publish on networks, as they are seen to be peers and, therefore, lacking commercial interests (Castelló, Del Pino & Tur, 2016; Kanellopoulos & Panagopoulos, 2008).

The scientific community has studied how social networks exercise an influence on the public, which is reflected in the reactions to one user's publications by other users. In general, the degree of success achieved on social media is denominated engagement (Muñoz-Expósito, Oviedo-García & Castellanos-Verdugo, 2017). Engagement is the result of a psychological state that leads to frequent interaction with the object on which the user is focused, which could be a brand or a celebrity (Thakur, 2018). It involves establishing a long-term relationship that is the result of motivational factors, both emotional and utilitarian, and which leads to favorable results for the objects at which it is directed, such as better brand evaluation (Hollebeek, Glynn & Brodie, 2014).

There is currently no consensus on how to measure engagement (Al-Yazidi, Berri, Al-Qurishi & Al-Alrubaian, 2020). In addition, each social network has its own idiosyncrasies, which means it is aimed at different audiences, and the way users interact with Social

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Media Influencers (SMIs) is also different. For example, TikTok users are mainly young people (Anderson, 2020) who glorify very young celebrities who publish dance videos, as is the case of Charlie D'Amelio (Kennedy, 2020). This means that an essential element for engagement on this network is the video playback completion rate, which is not true for other social networks (Xiao, Wang & Wang, 2019).

The literature has largely focused on studying engagement on Twitter. This network has been especially relevant as a means of exercising influence, especially since politicians like Donald Trump used it as a key tool for their campaigns (Kelm, Dohle & Bernhard, 2019). Although this network reached its height between 2010 and 2015, a report drafted by We Are Social & Hootsuite (2020) states that its community is still very active; furthermore, this platform performs a dual role: in addition to allowing users to share their experiences and opinions through tweets, it is a news circulation portal for thousands of young people, with more influence than the traditional media.

Apart from politics and journalism, there are also other professional and academic fields in which the use of Twitter is frequent. This is the case of researchers, who use Twitter to disseminate their research work and interact with other users of this network (Ortega, 2016). So much so that new metrics have emerged to evaluate the performance of researchers, giving way to what is known as altmetrics. This term is used to designate the new metrics that are proposed as a complement to traditional metrics, such as the impact factor used for scientific journals or the researcher's citation indexes such as the h-index (Bornmann, 2014; Priem, Taraborelli, Groth & Neylon, 2010). Among these alternative metrics is the engagement that academics generate on Twitter.

Engagement on Twitter has been studied in different ways. One of the most common approaches has been to identify influencers based on their capacity to disseminate messages. To do so, everything from simple metrics, such as those provided by Twitter's API, to more complex metrics based on mathematical network theory have been used (Al-Yazidi et al., 2020). The interactions influencers generate among other users have been used both to identify influencers and measure their engagement. These interactions include reactions such as likes, retweets, and replies.

Many researchers have measured interactions in absolute terms and for a specific period of time (Hazarika, Rea, Mousavi & Chen, 2021; Landreth Grau & Zotos, 2016; Mishori, Singh, Lin & Wei, 2019; Nason, O'kelly, Bouchier-Hayes, Quinlan & Manecksha, 2015; Olinski & Szamrowski, 2020; Prabhu & Rosenkrantz, 2015; Sanchez, 2018; Thackeray, Neiger, Smith & Van Wagenen, 2012). This method of measuring engagement is useful when the period of time during which data is collected is essential to the study, for example, if the study aims to measure engagement generated by politicians during an election campaign. However, this methodology would not be correct when the time period is not as important, as there would be a bias that would benefit more active users because their likelihood of generating reactions among other users would increase. For this reason, the vast majority of research performs this analysis in relative terms, measuring average reactions per tweet (Adi & Grigore, 2015; Bradley & James, 2019; Harrigan et al., 2021; Knox & Hara, 2021; Namkoong, Ro & Henderson, 2019; Shahbaznezhad & Rashidirad, 2021; Yang & Kim, 2017) or, to a lesser extent, per follower (Greene et al., 2021; Kaminski, Szymanska & Nowak, 2021; Veale et al., 2015). However, there is not a comprehensive measure of engagement that combines these two perspectives.

In this study, we propose measuring Twitter user engagement using a composite indicator, which evaluates this complex phenomenon based on the components that determine it. To do so, a mix of two approaches — by tweet and by follower — is proposed. This comprehensive approach corrects for the bias of the studies that only measure by tweet or by follower, as the former measure engagement based on user production and the latter measure engagement based on popularity. Measuring engagement according to these two approaches allows comparisons between both measures and draw relevant conclusions. Specifically, if a user has a higher engagement index in the by tweet approach than the by follower approach, this indicates that they have followers that do not react to their publications and/or that they receive reactions from other users who do not follow them. In other words, this means that their followers cannot be said to have a high degree of loyalty, but this user may be impacting other Twitter users instead. On the other hand, if engagement by follower is higher than by tweet, the opposite is true: i.e., their followers are active and show loyalty when the user publishes a tweet.

This study combines these two approaches by considering a series of indicators based on a review of the literature and applying the multicriteria TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method to obtain a composite indicator. TOPSIS classifies the units under evaluation based on two distances: proximity to the ideal profile and distance from the anti-ideal profile, and its application requires only assigning a weight to each indicator or component, which is minimally demanding compared to others more sophisticated methods that require adding more subjective information to rank options. Once the composite indicator is obtained, its utility is demonstrated by measuring the engagement of a group of SMIs, who have already been identified as such, and could even be considered celebrities. This practical application provides companies with a tool for decision-making in the influencer marketing sphere, as quantifying engagement allows them to compare expected impact according to each SMI's prestige.

2. Theoretical framework

2.1. Multicriteria analysis on social networks

Engagement is a multi-faceted phenomenon and must be evaluated using different measurement indicators that can reflect different aspects of that phenomenon. In this regard, it is appropriate to construct a composite index, as it allows for a simple comparison of a complex phenomenon (El Gibari, Gómez & Ruiz, 2018). The Joint Research Centre-European Commission (2008) defines the concept of composite index as an aggregate of all dimensions, objectives, individual indicators, and variables used. The construction of composite indices has become more widespread in recent years to measure different types of phenomena in different fields (sustainability, business, environment, etc.) and has been applied both in scientific settings, as well as in politics and socioeconomics.

Table 1
Twitter relationships between users and tweets.

	User	Tweet
User	Follows/ is followed byMentionReplies toRetweets toPosted by	PostsRetweetsLikesReplies
Tweet	Retweeted byLiked byReplied by	Replies / is replied fromRetweets / is retweeted from

Source: Riquelme and González-Cantergiani (2016).

In the scientific community, there is an extensive literature that analyzes different methodologies for constructing indexes and/or that proposes composite indices to measure complex phenomena, as demonstrated by the bibliographic revisions of Greco, Ishizaka, Menelaos and Torrisi (2019) and El Gibari, Gómez and Ruiz (2019). In the political and socioeconomic sphere, public and private organizations publish composite indexes annually that measure phenomena of interest. Thus, the Sustainable Development Goals index (SDG index) and the Inequality-adjusted Human Development Index (IHDI) are composite indices published annually by the UN. The World Economic Forum publishes the Travel and Tourism Competitiveness Index (TTCI) annually. And the magazine Fortune publishes the Fortune Corporate Reputation Index to measure business reputation.

There are two key issues when it comes to constructing a composite index: choosing the measurement indicators and applying a mathematical aggregation method (El Gibari et al., 2019). In regards to the latter aspect, it is important to select a mathematical method that allows for a robust classification to be obtained and which, at the same time, is easy to interpret (Lafortune, Fuller, Moreno, Schmidt-Traub & Kroll, 2018). In this sense, multicriteria methods perfectly align with the objective pursued in constructing a composite index. However, their application has been criticized for the need to provide some type of additional information associated with each indicator. This information can include assigning a weight to each indicator, or requesting more sophisticated information from the decision-maker, like setting reference values for each simple indicator, establishing a function of preference, etc.

TOPSIS is a multicriteria method based on distances, and classifies the elements being assessed by their proximity to the best value and their distance from the worst value of each indicator. It was proposed by Hwang and Yoon (1981). Behzadian, Otaghsara, Yazdani and Ignatius (2012) and Salih, Zaidan, Zaidan and Ahmed (2019) have performed exhaustive biographical analyses of the method, both in theoretical and applied versions. The TOPSIS method has already been applied in the field of social networks. Specifically, research by Gandhi and Muruganantham (2015), Zareie, Sheikhahmadi and Khamforoosh (2018), and Muruganantham and Gandhi (2020) employs TOPSIS to identify the users on a social network with the greatest influence, concluding that the use of the multicriteria analysis performs more accurately than the other methods. Given the above, it is surprising that this multicriteria analysis has not been used before as a tool to measure engagement.

2.2. Engagement indicators on twitter

Several types of indicators or metrics can be used to measure the success of a Twitter user. One metric is a measurement system that quantifies static or dynamic characteristics (Farris, Bendle, Pfeifer & Reibstein, 2006), and which is used to establish objectives, measure degrees of compliance or deviation and, subsequently, implement measures for improvement (Peters, Chen, Kaplan, Ognibeni & Pauwels, 2013). For these purposes, the classification developed by Riquelme and González-Cantergiani (2016) is especially useful. These authors distinguish between four types of relationships on Twitter: user to user, user to tweet, tweet to tweet, and tweet to user (see Table 1). Each one is linked to a series of indicators that measure the intensity of the relationship. Given that an essential component of engagement are users' reactions to the publication of a tweet, the appropriate indicators to use in this study are those established for the tweet to user relationship, i.e.: (1) How frequently are a user's tweets retweeted?; (2) How frequently are a user's tweets "liked"?; (3) How frequently do a user's tweets receive replies?

There is a broad consensus in terms of viewing likes and retweets of posts as fundamental indicators of engagement, since they express a positive attitude and help a message go viral, respectively (Aleti, Pallant, Tuan & van Laer, 2019; Casado-Molina, Rojas-de-Gracia, Alarcón-Urbistondo & Romero-Charneco, 2022; Didegah & Mejlgaard, 2018; Gibbs, O'Reilly & Brunette, 2014; Rojas-de-Gracia, 2019; Zhang et al., 2021). However, more controversial is the number of replies, in which a user is mentioned and a tweet that the user has posted is replied to. Although this could be considered an indicator of engagement in principle, some authors are not so convinced, given that the content would have to be analyzed to confirm that the reply represents a favorable reaction, as established in the definition of engagement. In fact, Enjolras, Steen-Johnsen and Wollebaek (2012) found that social networks in general are used by the public more often to oppose an idea than to support it. More specifically, in the case of Twitter, Enli and Skogerbø (2013) concluded that it was not the "friendliest" network, as it is often used to contradict and refute what is published, and even to insult. However, the fact that comments are made, whether positive or negative, continues to indicate a user's capacity to generate a reaction in others and, therefore, must be kept in mind to measure their influence.

Despite the above, to obtain a correct measurement of a tweet's degree of success based on interactions received by the user (like, retweets, and replies), the measurement must be relative, obtaining the average by tweet and by follower. When the ratio of these interactions is calculated by tweet, this measures the impact of a user's activity on the network in relation to their production. Thus, if two users publish the same number of tweets in a given period of time, and one user's tweets generate more reactions than the other's, it is obvious that the first user's engagement is higher than the second's. On the other hand, when the ratio of interactions is calculated by follower, this obtains a measurement of engagement relative to a user's popularity. To use a similar example as above, if two users have the same number of followers, but one generates more interactions with their publications than the other, then the

Table 2
Influence indicators according to the approach used.

Tweet approach Indicator	Description	Follower approach Indicator	Description
$x_{i1} = \frac{T_i}{d_i}$	Tweets per day	$x_{i6} = F_i$	Number of followers
$x_{i2} = \frac{L_i}{T_i}$	Likes per tweet	$x_{i7} = \frac{L_i}{F_i}$	Likes per follower
$x_{i3} = \frac{Rt_i}{T_i}$	Retweet per tweet	$x_{i8} = \frac{Rt_i}{F_i}$	Retweets per follower
$x_{i4} = \frac{Rp_i}{T_i}$	Replies per tweet	$x_{i9} = \frac{Rp_i}{F_i}$	Replies per follower
$x_{i5} = \Delta T_i$	Tweets in the last 30 days	$x_{i10} = \Delta F_i$	Followers in the last 30 days

Source: Own elaboration.

latter would be said to have less engagement, regardless of the number of tweets that these two users published. Therefore both ways of measuring engagement, i.e., both approaches, are necessary to assess engagement from different points of view.

Moreover, aside from using the number of followers and the number of tweets to gage interactions, the value of these metrics in and of themselves offers valuable information to quantify engagement on Twitter. In the case of followers, it should be noted that the idea that a large number of followers equals popularity has been criticized for its simplicity (Cha, Haddadi, Benevenuto & Gummadi, 2010; Freberg, Graham, Mcgaughey & Freberg, 2011; Silva & de Brito, 2020). However, we believe that the number of followers must be taken into account as an indicator and as a measurement instrument in relative terms. Indeed, there are Twitter users who assiduously read publications and leave no trace on the network. In this case, the only way to measure this influence is through the number of followers (Riquelme & González-Cantergiani, 2016), as they are the most likely to read the publications of the users they follow.

In terms of production, i.e., the number of tweets per day, a distinction must be made between the tweets the user wrote themselves and the tweets that the user retweeted from others. Although both appear on their profile and can be read by their followers, it is logical to view true activity as that generated by original messages. This activity on social media increases visibility and strengthens the feeling of belonging to a virtual community, by establishing ongoing communication with a group of individuals with common interests (Masood & Abbasi, 2021; Palazón, Sicilia & Delgado, 2014; Sicilia & Palazón, 2008). Although there are no clear studies that indicate that greater activity on Twitter by SMIs increases their capacity to connect with the audience they are addressing, some research points in that direction, especially in politics. According to these articles, political leaders who wish to increase the visibility of their campaigns and parties in the public sphere believe it is essential to show constant activity and dialog on Twitter (Enli & Skogerbø, 2013; Karlsen, 2011). Even Rojas-de-Gracia (2019) concludes that the most active political leader on social networks gets the highest number of likes and retweets. Also along these lines, although outside of politics, Rui, Liu and Whinston (2013) found that the number of tweets about a movie is a strong predictor of its future economic performance.

There is another aspect related to these last two indicators, the number of followers and the number of tweets, that must be kept in mind when measuring a user's influence, which is their relevance or, to put it another way, whether they are "in fashion." To that end, indicators such as the number of followers added (or lost) in the last 30 days, or the number of tweets published in the last 30 days on social media have been used by authors in their research to study brand and user behavior (Champagnat, 2018; Earnshaw, 2017). One indication of the importance of topicality when evaluating the relevance of a company and, therefore, of a celebrity, is that the prestigious Fortune magazine, which compiles a list each year of the most important corporations in the United States (Fortune 500), assesses, among other aspects, a company's social media presence. It defines a company as having a social media presence if they have an active account; to qualify as such, they must have made at least one publication in the last 30 days.

In summary, based on a review of the literature, this study proposes applying the TOPSIS method to create a composite index to show users' engagement based on the 10 indicators described in Table 2. These 10 indicators are grouped into two approaches: by tweet and by follower. Therefore, the objective is to measure user engagement on Twitter from a comprehensive perspective. Additionally, to illustrate the procedure, we measure the engagement of a group of SMIs on Twitter whose status as influencer is fully consolidated.

3. Methodology

The TOPSIS multicriteria method is based on the idea of choosing the alternative that is closest to the ideal point and furthest from the anti-ideal point. The ideal point is comprised of the best value for each indicator and the anti-ideal comprises the worst value. In general, the ideal and anti-ideal points are two "virtual alternatives," since very rarely is there an alternative that is the best or the worst on all indicators. Let m be the number of users being studied and n the number of indicators or criteria (in our case, $n = 10$). Let $A = \{A_1, A_2, \ldots, A_m\}$ be the set of users and let $C_1, C_2, \ldots, C_n$ be the indicators with which they will be evaluated. We use x_{ij} to denote the value of user A_i with respect to indicator C_j. Without loss of generality, let us suppose that all indicators are of the "more is better" type. The steps for this method are as follows:

Step 1: Normalize the value of each user for each indicator, using the L2 or Euclidean norm:

$$y_{ij} = \frac{x_{ij}}{\sqrt{\sum_1^m x_{ij}^2}}, i = 1, 2, \ldots, m; \; j = 1, 2, \ldots, n.$$

Step 2: Obtain the normalized decision matrix. The decision-maker establishes a weight for each indicator ($w_j > 0,\ j = 1,\ 2,\ \dots,\ n,\ \sum_{j=1}^{n} w_j = 1$). Calculate the elements of the normalized matrix:

$$v_{ij} = w_j \cdot y_{ij},\ i = 1,\ 2,\ \dots,\ m;\ j = 1,\ 2,\ \dots,\ n.$$

Choose the best and worst value for each indicator and construct the ideal alternative, $\mathbf{v}^+$, and the anti-ideal alternative, $\mathbf{v}^-$. Given that we want to maximize all indicators, the best value for each is the maximum value $v_j^+ = v_{ij}$, and the worst is the minimum, $v_j^- = v_{ij}$:

$$\mathbf{v}^+ = \left(v_1^+, \dots, v_n^+\right), \mathbf{v}^- = \left(v_1^-, \dots, v_n^-\right)$$

Step 3: Calculate the weighted distance for each alternative from the ideal and anti-ideal points, using a measure of distance, like L_2 or Euclidean distance:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_j^+ - v_{ij}\right)^2},\ \ D_i^- = \sqrt{\sum_{j=1}^{n} \left(v_j^- - v_{ij}\right)^2},\ i = 1,\ \dots,\ m$$

It is verified that $0 \le D_i^+,\ D_i^- \le 1$.

Step 4: For each alternative, calculate the relative closeness coefficient, C_i, as follows

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-},\ i = 1,\ 2,\ \dots,\ m.$$

The relative closeness coefficient is a value between 0 and 1. A C_i value close to 1 indicates that the alternative is close to the ideal point, and far from the anti-ideal point.

Step 5: Order the options according to the relative closeness coefficient, C_i, in descending order, since if $C_i > C_k,\ i, k = 1,\ 2,\ \dots,\ m$, then A_i is preferable to A_k.

To sum up, the three ideas upon which TOPSIS is based are: 1) Define two artificial user profiles: the ideal user, who is assigned the best value for each indicator, and the anti-ideal user, who has the worst values for each indicator. 2) For each user, calculate the distance to the ideal profile and the distance to the anti-ideal profile. Obviously, a user will be better the closer they are to the ideal and the further they are from the anti-ideal. Therefore, we can identify a user's strength as its distance from the anti-ideal (distance to maximize) and its closeness to the ideal (distance to minimize). 3) Order based on the relative closeness coefficient, which is calculated by dividing the distance to the anti-ideal by the sum of the distance to the ideal and the distance to the anti-ideal. This value will be between 0 and 1. If a user is close to the ideal and far from the anti-ideal, it will have a D_i^+ value close to zero and a D_i^- value close to 1, so the quotient $\frac{D_i^-}{D_i^+ + D_i^-}$ will be close to the value 1. Therefore, high values of this coefficient are preferable, since if the distance to the ideal is small and the distance to the anti-ideal is large, the value will be close to 1; on the contrary, the value will be close to 0.

4. An application to social media influencers

Below the composite index is applied to a group of influencers from Spain. To obtain the group of influencers, the list that Forbes magazine published on the 100 best influencers in Spain 2020 was used (Forbes, 2020); therefore, this group can be considered true celebrities. The Spain list was chosen because the heterogeneity of different cultural contexts led the researchers to limit ourselves to a single country. We believe this makes sense because an influencer in one country could be a total unknown in another. Moreover, we chose Spain because it is the authors' native country, which allows for an interpretation of the results with greater knowledge of the context.

The Forbes list does not establish a hierarchy as such, but lists the 10 top influencers in each sector, distinguishing between 10 sectors: Beauty (Be), Business (Bu), Fashion (F), Gastronomy (G), Lifestyle (L), Motor (M), Sport and Fitness (S), Technology (Te), Tourism and Travel (To), and Videogames (V). However, ultimately only 60 influencers were analyzed, as the rest did not have a Twitter account, or the account was inactive in the last three months at the time data was collected, which was from November 12 to 14, 2020. Table 3 summarizes the number of SMIs included in the sample, divided by sector and gender. On the rare occasion that there was a group of influencers behind a Twitter account rather than a single influencer, the gender of the most visible face was chosen, except for an account in the Tourism and Travel sector, which is jointly managed by a man and woman.

The application Twitonomy was used to collect data. This pay-to-use tool allows users to extract the last 3200 tweets from any Twitter account, indicating the date and time of publication for each. The publications by SMIs that were retweets of other users were discarded. Ultimately, 144,989 tweets were analyzed, which is an average of 2416 tweets per SMI. Twitonomy directly provides the following data: number of tweets (T_i), of followers (F_i), of likes (L_i), and of retweets (Rt_i). The application does not provide the number of replies (Rp_i), but it does show which were the five most retweeted tweets. For this indicator, we used the average number of replies for those five tweets as a proxy. Then, the relative indicators were calculated: tweets per day ($x_{i1} = \frac{T_i}{d_i}$), where d_i is the number of days in the period analyzed for the i th SMI; number of followers ($x_{i6} = F_i$), likes per tweet ($x_{i2} = \frac{L_i}{T_i}$), and per follower ($x_{i7} = \frac{L_i}{F_i}$); retweets per tweet ($x_{i3} = \frac{Rt_i}{T_i}$), and per follower, ($x_{i8} = \frac{Rt_i}{F_i}$), and replies per tweet ($x_{i4} = \frac{Rp_i}{T_i}$), and per follower, ($x_{i9} = \frac{Rp_i}{F_i}$).

Table 3
Sector and sex of the influencers analyzed and discarded from the sample.

Sector	Total by gender Male	Female	Total	Included in the sample Male	Female	Total	Discarded from the sample Male	Female	Total
Beauty	1	9	10	1	4	5	–	5	5
Business	9	1	10	9	1	10	–	–	–
Fashion	5	5	10	2	1	3	3	4	7
Gastronomy	5	5	10	2	2	4	3	3	6
Lifestyle	2	8	10	2	1	3	–	7	7
Motor	8	2	10	7	1	8	1	1	2
Sport and Fitness	4	6	10	2	1	3	2	5	7
Technology	8	2	10	8	2	10	–	–	–
Tourism and Travel	7.5*	2.5*	10	3.5*	1.5*	5	4	1	5
Videogames	8	2	10	8	1	9	–	1	1
Total	**57.5***	**42.5***	**100**	**44.5***	**15.5***	**60**	**13**	**27**	**40**

*The half point is due to an account that is managed jointly by a man and a woman.

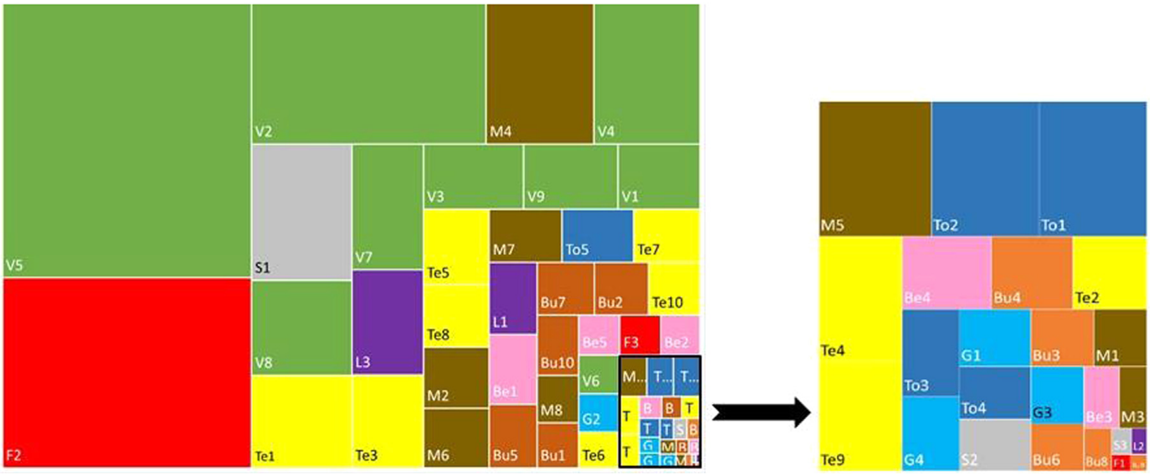

Fig. 1. Treemap chart of influencer performance.

Lastly, the information on variation in tweets ($x_{i5} = \Delta T_i$) and followers ($x_{i10} = \Delta F_i$) for the last 30 days was obtained from the website SocialBlade (https://socialblade.com/twitter/).

Mathematically, we can express our composite index proposal as follows:

$$C_i = C_i\left(\frac{T_i}{d_i}, \frac{L_i}{T_i}, \frac{Rt_i}{T_i}, \frac{Rp_i}{T_i}, \Delta T_i, F_i, \frac{L_i}{F_i}, \frac{Rt_i}{F_i}, \frac{Rp_i}{F_i}, \Delta F_i\right)$$

where C_i is the relative closeness coefficient from the TOPSIS method. These calculations can be performed using a spreadsheet, a specific software such as DECERNS (Yatsalo, Didenko, Gritsyuk & Sullivan, 2015), or some free tool like the TOPSIS package (Yazdi, 2013) based on software R (R Core Team, 2021) or the python-based tool PyTOPS (Yadav, Karmakar, Kalbar & Dikshit, 2019).

As described in the methodology, this method requires a weight to be assigned to each indicator. In this study, the same weight was assigned to all the indicators, as there is a lack of robust empirical evidence to suggest that some are more important than others. The requirement of establishing a weight for each indicator is both an advantage and disadvantage. The advantage is the freedom of the decision-maker to give greater importance to one criterion over another depending on the context in which the composite index is to be applied. The disadvantage is the subjectivity involved in assigning one weight or another. To mitigate this disadvantage, a weight sensitivity analysis can be performed to determine how changes in the weights affect the value of the composite indicator. Thus, if the change in weights results in large shifts in the ranking, different solutions could be adopted, such as consulting various experts in the field in which the proposed index will be applied.

Table 4 presents the results obtained from applying TOPSIS to the 60 SMIs analyzed. To identify them, they were assigned a name consisting of the first one or two letters of the sector they belong to, followed by a digit. The influencers are ordered according to their position in the ranking, based on the value of the relative closeness coefficient, C_i. Columns 3 and 4 show the distance of each influencer from the anti-ideal (D_i^-) and the distance to the ideal (D_i^+), respectively. Influencer V5 is at the top of the ranking, as he presents the greatest distance to the anti-ideal (D_i^-) and the shortest distance to the ideal (D_i^+), followed by F2 and V2. The comparison between the latter two shows that F2 is further from the anti-ideal than V2, but, in turn, V2 is closer to the ideal than F2. In these types of situations, the C_i ratio establishes an order of alternatives, weighing the relative importance of one distance

Table 4
Performance of influencers.

Influencer	C_i(Max)	D_i^-(Max)	D_i^+(Min)	Influencer	C_i(Max)	D_i^-(Max)	D_i^+(Min)
V5	0.5539858	0.0200291	0.0161254	**Be5**	0.0132010	0.0004918	0.0367652
F2	0.3812832	0.0127962	0.0207646	**F3**	0.0130812	0.0004643	0.0350292
V2	0.2690684	0.0071270	0.0193607	**Be2**	0.0125942	0.0004450	0.0348873
M4	0.1235178	0.0044674	0.0317004	**V6**	0.0124853	0.0004714	0.0372842
V4	0.1214180	0.0044561	0.0322444	**G2**	0.0122926	0.0004441	0.0356866
S1	0.1098602	0.0040358	0.0327003	**Te6**	0.0117135	0.0004429	0.0373721
V8	0.0765944	0.0024418	0.0294378	**M5**	0.0092350	0.0003338	0.0358145
Te1	0.0747755	0.0026906	0.0332922	**To2**	0.0088369	0.0003156	0.0353932
V7	0.0725582	0.0021832	0.0279058	**To1**	0.0088263	0.0003135	0.0352028
L3	0.0604952	0.0019474	0.0302429	**Te4**	0.0063480	0.0002378	0.0372292
Te3	0.0537955	0.0018109	0.0318515	**Te9**	0.0055330	0.0002059	0.0370073
V3	0.0524944	0.0018897	0.0341093	**Be4**	0.0039428	0.0001458	0.0368408
V9	0.0493591	0.0017228	0.0331800	**Bu4**	0.0035971	0.0001355	0.0375337
V1	0.0427901	0.0014757	0.0330105	**Te2**	0.0032566	0.0001227	0.0375642
Te5	0.0403777	0.0015050	0.0357689	**To3**	0.0030504	0.0001133	0.0370218
Te8	0.0328091	0.0011467	0.0338051	**G4**	0.0025886	0.0000991	0.0381698
M2	0.0323366	0.0011212	0.0335509	**G1**	0.0024894	0.0000932	0.0373302
M6	0.0315980	0.0010540	0.0323011	**To4**	0.0022763	0.0000868	0.0380373
M7	0.0310546	0.0011280	0.0351967	**S2**	0.0022361	0.0000834	0.0372296
To5	0.0305786	0.0010706	0.0339416	**Bu3**	0.0022040	0.0000843	0.0381538
Te7	0.0282793	0.0010245	0.0352048	**M1**	0.0018594	0.0000700	0.0375968
L1	0.0277559	0.0009309	0.0326069	**G3**	0.0018478	0.0000708	0.0382711
Be1	0.0266707	0.0008905	0.0324965	**Bu6**	0.0015234	0.0000590	0.0386954
Bu5	0.0245089	0.0008736	0.0347696	**Be3**	0.0013161	0.0000499	0.0378708
Bu7	0.0244199	0.0008425	0.0336591	**M3**	0.0010446	0.0000404	0.0386355
Bu2	0.0231620	0.0008736	0.0368417	**Bu8**	0.0007268	0.0000281	0.0386574
Te10	0.0218839	0.0007482	0.0334394	**S3**	0.0003136	0.0000122	0.0388404
Bu10	0.0202697	0.0007528	0.0363857	**L2**	0.0002520	0.0000099	0.0393037
M8	0.0160129	0.0005512	0.0338727	**F1**	0.0001875	0.0000074	0.0392804
Bu1	0.0151883	0.0005755	0.0373186	**Bu9**	0.0001646	0.0000064	0.0391353

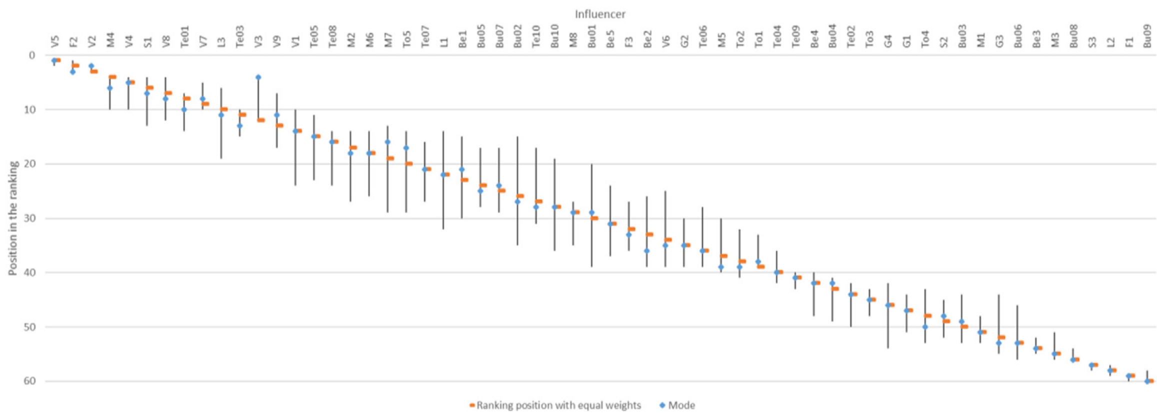

Fig. 2. Weight sensitivity analysis.

compared to the other. At the bottom of the ranking are influencers L2, F1, and B9, who presented almost non-existent distances from the anti-ideal and the greatest distances to the ideal.

Another important aspect in the ranking is the relative value of each influencer's relative closeness coefficient compared to the rest. The first (V5) has a relative closeness coefficient of 0.554, more than double the third (V2) and five times higher than the fifth (V4). After V4, the value of the relative closeness coefficient begins to decrease at a much slower rate. The performance of the first four SMIs in the ranking is much higher than the rest. This is very clearly shown in Fig. 1, which uses a treemap chart to display the value for each influencer's performance. If we look at the largest rectangles, we see that the color green (videogame sector) predominates, while the color yellow (technology) is more prominent in the medium-size rectangles. In the smallest rectangles, the colors orange (business), dark blue (tourism), and light blue (gastronomy) predominate. However, it must be remembered that the number of SMIs in each sector is different and, therefore, the data must be analyzed in relative terms in order to draw any conclusions.

To supplement this analysis, a weight sensitivity analysis was performed using Pytops (Yadav et al., 2019), with a variation of ±25% in the weights, generating 2500 vectors with different weights. The results of these simulations are shown in Fig. 2, where the x-axis shows the order of influencers in the equal weights scenario, and the y-axis shows the range of positions obtained across all of

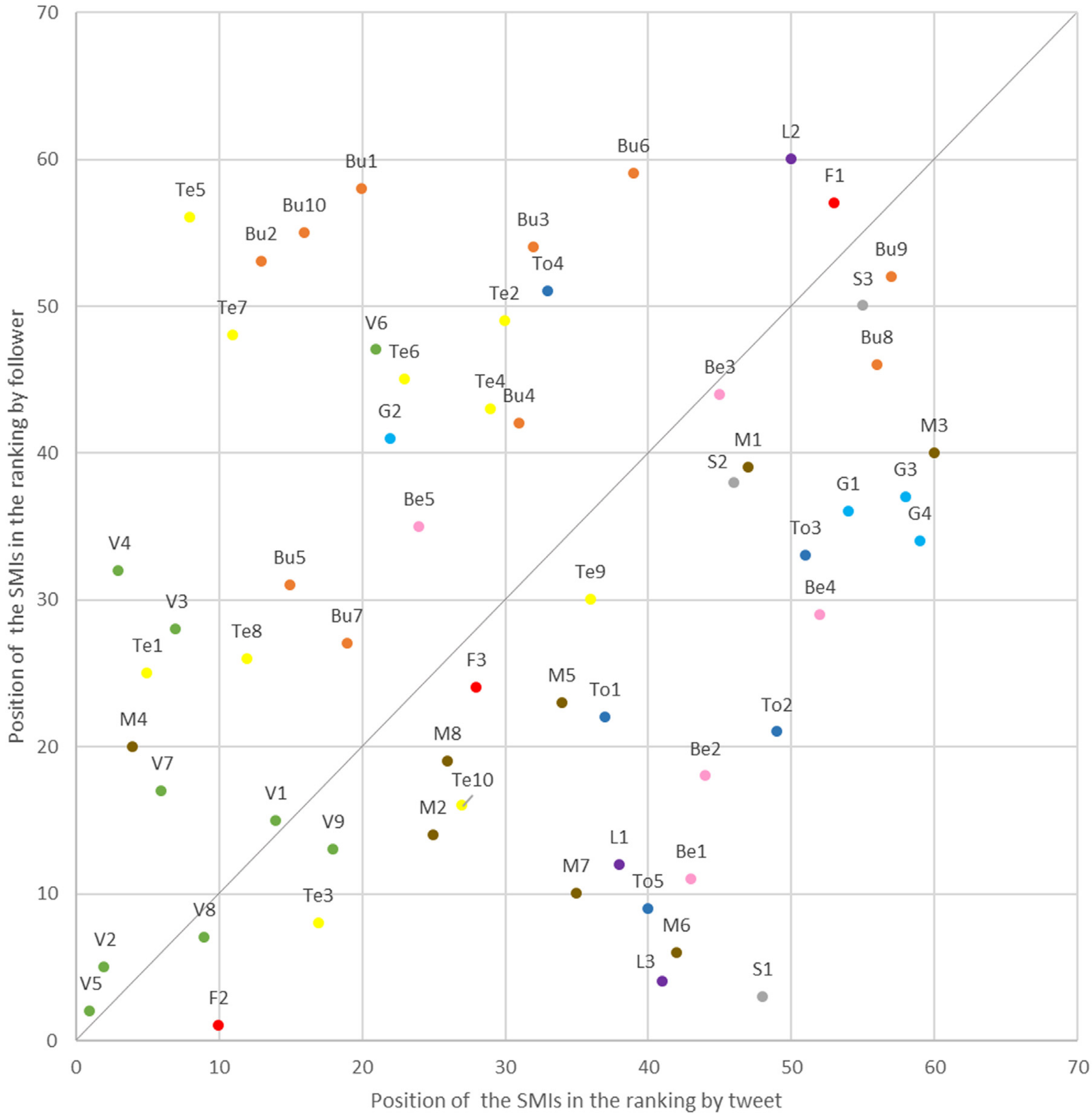

Fig. 3. Individual rankings by tweet versus by follower.

the simulations, such that the vertical line shows the variation in positions in all 2500 simulations. For example, the vertical line for influencer M4 (fourth position on the x-axis) varies between 4 and 10, which indicates that this influencer's positions in the rankings across all of the simulations were between these two values.

The graph also shows the SMI's position in the ranking with equal weights (orange marker) and the modal value, i.e., the position in the ranking that the influencer most frequently occupied in all of the simulations (blue dot). In general, these two values are very close for almost all the SMIs; they were the same for 48% of the influencers and there was a difference of one position for 33.3%. This sensitivity analysis offered an interesting result: the influencers in the first and last positions generally had a lower range of variation than the others. Therefore, this analysis confirms that the variation in weights does not have a significant influence on the final ranking, especially at its extremes.

Furthermore, in this ranking the use of the two approaches to analyzing performance, indicators related to the number of tweets (production) and indicators related to the number of followers (popularity), allows for an analysis of whether there would be differences in the ranking when the approaches are applied separately. The results are shown in Fig. 3 in a point cloud. The horizontal axis shows the position of each SMI by tweet, and the vertical axis shows the position according to followers. The bisector divides the plane in two areas: to the left are the SMIs who are better positioned when analyzing solely by tweet, i.e., without considering the criteria by follower, while on the right the opposite is true.

As can be seen, there are important changes in position between the two rankings. Just five influencers (BE3, V1, V2, V5, and V8) have variations of three positions or less, while 10 SMIs fluctuate over 30 positions, up to 48 positions for influencer TE5. Therefore, it is clear that in this specific case to which we are applying the composite index, each approach measures specific characteristics of performance, reinforcing the idea that both should be considered when building the composite index to measure SMI engagement on Twitter.

5. Conclusions

This study proposes the construction of a composite index to measure user engagement on Twitter using TOPSIS, a multicriteria method that bases its ranking on minimizing the distance to the ideal point and maximizing the distance to the anti-ideal. To do so, a mix of indicators based on two approaches is proposed: the tweet approach, and the follower approach. The former reflects engagement based on user production, and the latter measures engagement by popularity. The results show the suitability and pertinence of both, as it is confirmed that they measure different, yet necessary aspects for offering a holistic view of the engagement generated by a Twitter user; this is a new finding compared to prior studies, which only focused on one approach or the other.

The contributions of this work are not only focused on the methodological component, but they also allow for conclusions to be drawn from its practical application. First, this work offers an affordable tool that could be of use to academics, marketing professionals who wish to collaborate with SMIs for their campaigns, and, obviously, to influencers themselves, who can use these results as a way of assessing their performance. Additionally, this tool can be used by organizations and institutions with a Twitter presence that would like to both quantify their degree of engagement in a comprehensive fashion and identify where that engagement is coming from: followers or other users.

We are aware that the sample to which the composite index has been applied is limited, both in context — as it corresponds to a very specific culture and network — and in size. However, this contextualization was seen as necessary, as SMIs are not necessarily the same in every country; therefore, it would be interesting to explore users' behavior in different countries. Moreover, the methodology proposed in this study could be adapted to other similar social networks such as Facebook, Instagram, YouTube, and TikTok to offer a more complete, valuable perspective for the field of influencer marketing. It can even be extended to other types of users and to strictly professional social networks (e.g. LinkedIn or ResearchGate). Specifically, the application of this index in the field of research can be very relevant, given the importance of measuring the impact of the work of academics. In fact, considering that Twitter is one of the most used social networks by them (Ortega, 2016), the proposed index can contribute to the field of altmetrics without more than replacing the group of users analyzed in this work by that of the researchers with a Twitter account.

Furthermore, the sample size also invites other future lines of research using the proposed composite index to explore other aspects. For example, Table 3 shows that the Twitter presence of SMIs is unequal both in terms of gender and sector. Moreover, Fig. 1 indicates that some sectors, such as videogames, have a very high level of engagement, while others, like gastronomy, have very low levels. Is this behavior due to a specific factor corresponding to this sample? Or is it a general trend on Twitter?

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María M. Muñoz: Conceptualization, Methodology, Formal analysis, Writing – original draft. **María-Mercedes Rojas-de-Gracia:** Conceptualization, Methodology, Validation, Writing – original draft. **Carlos Navas-Sarasola:** Data curation.

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