Business, Economics and Management Research Journal 5(3) 266-285

BEMAREJ | Business, Economics & Management Research Journal

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An MCDM approach to evaluating companies' social media metrics based on user-generated content

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Abstract

User-generated content (UGC) has become one of the main factors that impacts companies, from consumers' purchase intentions to sales. This study proposes an MCDM approach to evaluate companies' social media metrics based on UGC. UGC metrics were defined and calculated as ratios based on each tweet's sentiment type (positive, negative, or neutral) and relevant metrics (tweet, retweet, favorite, and reach). Data was gathered from Twitter about six companies operating in cosmetics, marketplace, and electronics. MCDM techniques were conducted in the R programming language, namely CRITIC for obtaining criteria weights and ARAS and COPRAS for ranking the companies. The findings of this study contribute to improving the ranking of companies through UGC and extend the literature on the subject. MCDM techniques are recommended to be used effectively to evaluate companies' social media metrics since this approach considers several attributes altogether. R codes for data analysis are also provided in the appendix.

Keywords: Social Media, User-Generated Content, CRITIC, ARAS, COPRAS

JEL Codes: C02, C30, C44, L81, M19

1. Introduction

The popularity of social media and its applications is increasing day by day. Apart from the use of individual purposes such as entertainment, communication, or leisure, different groups or institutions want to successfully maintain their presence on social media. Social media platforms empower their users to be both content producers and consumers, laying the groundwork for them to express their opinions and feelings and receive support from other users. Companies, on the other hand, can monitor UGC and engage in a variety of activities. The impact of social media has spread to a wide range of areas. Social media data is viewed as an opportunity in advertising, public relations, customer relationship management, and business intelligence activities (Stieglitz et al., 2014).

Social media platforms vary in their interactive and egalitarian environments compared to other media (Peters et al., 2013). Users can decide what to generate and disseminate on social media platforms, which has been described as a "fundamental shift in power" (Safko, 2012). People use social media to find a new fancy restaurant, plan a vacation, find a movie or a song, check the reputations of people or institutions, and find information or reviews about a product or service (Anderson et al., 2015).

The pervasiveness of social media and UGC is undeniable, as evidenced by global statistics provided by Hootsuite and We Are Social (2021), which show that there are 4.20 billion active social media users worldwide (53.60% of the global population). Social media, according to the same report, is used for a variety of purposes, including business-related activities. Searching for brand information on social media accounts for nearly half of all searches, and it is even higher among Gen Z users, demonstrating the power of social media for younger generations. 28.2% of internet users say that they discover brands and products through social media ads while 24.4% learn about them through recommendations or comments on social media. These statistics demonstrate the unique power of social media and UGC.

Due to its great importance and impact on various aspects, how companies manage social media and appreciate UGC has become a critical issue. Companies should monitor their social media presence and

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Research Article

Received Date: 06.06.2022
Acceptance Date: 03.11.2022

take appropriate action as needed. Since social media platforms contain various metrics and it is necessary to consider more than one criterion at the same time to manage them, it is considered appropriate to use Multi-Criteria Decision Making (MCDM) techniques in this area. In the literature, there are some studies that have discussed social media metrics, ranging from the return on investment (ROI) of social media to dashboards and frameworks. In addition, there are some tools and platforms that perform ranking, but these platforms may not provide much information about the calculation process, relevant metrics, and their importance (criteria weights). Moreover, there are only a few studies in the literature on social media-based company or institution rankings (Capatina et al., 2018; Irfan et al., 2018), and MCDM methods are not applied in these studies. The current study seeks to fill this gap by proposing an MCDM approach to determining the weights of social media platform (Twitter) metrics and ranking companies based on brand-related UGC without directly discussing ROI or the "successful performance" of companies' social media efforts.

For the study, CRITIC, one of the objective criteria weighting methods, is preferred as the criteria weights are obtained by considering the correlation coefficient and the standard deviation at the same time. The reason for not using a subjective method is that discussions about the reliability of the results obtained from these methods still continue (Kazan & Özdemir, 2019). ARAS and COPRAS are chosen to rank the performance of decision alternatives. It is considered that the ARAS method would generate more precise findings since it is preferable in terms of revealing the proportional similarity of each decision alternative to the optimum alternative (Zavadskas & Turskis, 2010). The COPRAS method is chosen because it shows the utility degree of the alternatives compared to other methods (Zavadskas et al., 1994). Besides methods such as AHP and ANP, the reason why these two methods are preferred is that the calculations can be applied in a simpler and more practical way. In addition, the problem of inconsistency has been eliminated by not choosing a method based on pairwise comparisons such as AHP in the decision matrix. Furthermore, since these techniques have never been applied to social media studies to the best of the authors' knowledge, they are selected as an MCDM methodology for this study to demonstrate that they are successfully applicable in this field. To contribute to the implementation phase of the methods used in this study, the codes for the methods are developed by the authors in the R program. In this way, it is aimed to contribute to more practical and error-free calculations instead of manual or other calculations for problems with many criteria and alternatives.

This paper begins with a literature review related to social media, UGC and their importance from a business perspective. It will then provide social media metrics and measurement, as well as MCDM approaches to social media research. The methodology section discusses how the social media platform and companies were chosen, the data collection process, Twitter metrics based on UGC, and data analysis methods. The Twitter case study is carried out and the findings are presented. In the final section, conclusion and suggestions are provided. R codes for the analysis (CRITIC, ARAS and COPRAS methods) are also provided in the appendix.

2. Literature Review

Web 2.0 and User-Generated Content (UGC) terms are frequently used with social media. Web 2.0 can be considered as the ideological and technological foundation of social media, whereas UGC is the output that is generated and shared on social media (Kaplan & Haenlein, 2010). UGC can be defined as any output generated by users of an online digital system, shared by the same user through independent channels, that creates an impact with an individual or collaborative contribution (dos Santos, 2021). Apart from its two-way communication (dialogic) environment, social media is almost impossible to be controlled and users can easily coordinate through social media platforms (Lee et al., 2013). Customers who have a negative experience with a company's product or service can easily express their thoughts and feelings on social media, as well as receive approval or support. UGC has been embraced as a powerful novel tool in brand marketing, even though it can lead to a loss of control of a brand and the sharing of negative sentiments (Malthouse et al., 2016).

Brand-related UGC is created and consumed for different motivations. Shao (2009) states that people consume UGC to fulfill their informational, entertainment, and mood management needs. Liu et al.

(2017) investigate brand-related UGC topics on Twitter and find that the majority of the tweets were about products, service, and promotions, and others were related to competitors, news, and location. In addition, the impact of UGC on various areas has been investigated, such as brand equity (Christodoulides et al., 2012), sales (Dhar & Chang, 2009), product development (Ho-Dac, 2020), purchase intention (Malthouse et al., 2016), and stock performance (Tirunillai & Tellis, 2012).

Businesses use social media for a variety of purposes, including monitoring customer needs, engaging and serving customers, and listening to market trends (Nair, 2011). Social media usage has a positive impact on organizations. It can lead to lower marketing and customer service costs, better customer relationships, and easier access to customer and competitor information (Tajudeen et al., 2018). Oh et al. (2017) investigate the effects of social media and find that online customer engagement behavior has an impact on economic performance. Being present on social media can also help to increase brand awareness with the right social media management strategy.

2.1. Social Media Metrics and Measurement

The literature on social media and UGC highlights several reasons to deal with social media metrics and conduct social media measurement. Due to its unique features, social media should be measured differently than traditional media. Companies are recommended to set social media objectives and measure their success by defined metrics such as the number of followers, page views, and mentions (Aichner & Jacob, 2015). Several studies have been conducted to date on measuring and suggesting social media metrics concerning ROI (return on investment), KPIs (key performance indicators), and guidelines for dashboards and frameworks.

There are different approaches to measuring the ROI of social media. Hoffman and Fodor (2010) propose a framework for measuring social media activity that includes specific metrics for each social media platform. The metrics for the Twitter platform in the study are given in Table 1.

Table 1. Relevant Metrics of Twitter for Different Objectives

Social Media	Brand Awareness	Brand Engagement	Word of Mouth
Microblogging (e.g., Twitter)	number of tweets about the brand valence of tweets +/- number of followers	number of followers number of @replies	number of retweets

Hoffman and Fodor (2010) emphasize that in the social media environment where users have control, goals can be considered as an investment in customers and should be measured accordingly. This user-centered ROI focus is supported by Michopoulou and Moisa (2019) and Silva et al. (2020). The ROI on social media is not expected to be monetary. On the contrary, it is associated with customer-oriented metrics such as new followers, the volume of likes, comments, shares, and engagement rates.

Retweeting, forwarding content generated by others to one's network, is laden with potential as it helps reach more people and gives a higher endorsement (Malhotra, 2012). According to Sterne (2010), users retweeting companies' posts demonstrates that the content that a company shares with its target audience is owned by others who voluntarily want to disseminate it. Other metrics, such as the number of followers of users who retweet the company's tweets, can be measured in addition to retweet activity. This may aid in estimating the number of users who possibly see the content.

Peters et al. (2013) suggest guidelines for social media metrics and dashboards. One of the guidelines, "Shift from Quantity to Quality", states that quality is what matters. Different interactions, such as the number of fans, comments, likes, and shares, are tracked by social media dashboards. Stich et al. (2015) propose a social media framework for customer service based on six KPIs, namely, customer experience, customer interaction, customer satisfaction, customer activation, reach, and finance. Cvijikj et al. (2013) develop a framework for social media brand presence. The components of the framework are user analysis, UGC analysis, engagement analysis, and benchmarking. Murdough (2009) proposes a continuous and iterative process to define the main stages of the social media measurement process which begins with defining goals, identifying KPIs and performance benchmarks, and ends with reporting and providing insights to evaluate social media performance (e.g., social dashboard).

There are social media analytical tools that provide dashboards, reports of metrics, and insights for companies. Some are built-in services of social media platforms, such as Twitter Analytics, while others are paid tools, such as Hootsuite, Brandwatch, and SocialBakers. Some of these platforms provide rankings of companies, institutions, celebrities, and other entities based on social media metrics. Capatina et al. (2018) rank brands based on Facebook data from the Socialbakers and Social Mention platforms using a fuzzy-set qualitative comparative analysis. The criteria for the analysis are strength (the likelihood that a brand is discussed in social media), sentiment (the ratio of mentions that are generally positive to those that are generally negative), passion (the likelihood that users who talk about a brand will do so repeatedly), and reach (the number of users referencing a brand divided by the total number of mentions). In another study, universities' Facebook engagements are ranked based on total page likes, total number of posts, and total engagement (Irfan et al., 2018).

2.2. MCDM Approaches to Social Media Research

Social media platforms involve a variety of metrics and dealing with them requires considering multiple criteria at once. Similarly, companies encounter a wide range of problems on a daily basis and attempt to solve them by making the best decision. There are several methods for solving decision-making problems in the literature. The purpose of these methods, known as Multi-Criteria Decision Making (MCDM) techniques, is to rank the decision alternatives based on the determined criteria or to choose the best alternative. MCDM methods have a wide range of applications, including environmental management, transportation and logistics, business and financial management, project management and evaluation, and social service (Toloie-Eshlaghy & Homayonfar, 2011). Some of the MCDM methods are used for weighting criteria (e.g., DEMATEL, CRITIC, and SWARA), some for determining the performance of decision alternatives (e.g., TOPSIS, VIKOR, ARAS, COPRAS, and EDAS), and some for both situations (e.g., AHP).

On social media, rather than companies' messages, users trust other users' opinions, especially those who have experience with companies' products or services. Muruganantham and Gandhi (2020) propose an MCDM-based framework for the identification of influencers on social media by applying the TOPSIS method to a Twitter dataset. The results are compared with standard centrality measures and the proposed model outperformed the standard ones. Tsai et al. (2021) highlight the crucial role that bloggers play in hotel industry and apply a mixed MCDM model to assist managers in selecting bloggers. Importance-performance analysis (IPA), analytic hierarchy process (AHP), and the technique for order preference by similarity to ideal solution (TOPSIS) are utilized in the study.

The problem of selecting social media platforms implies dealing with complex multi-criteria. Tavana et al. (2013) integrate the ANP with fuzzy set theory and the COPRAS-G method to select the most suitable social media platform. The ANP and fuzzy set theory are applied to obtain the weights, and the COPRAS-G method is used to rank the platforms. In another study, Çalık (2020) applies MCDM methods to investigate the selection of social media platforms for a travel agency. The Best-Worst method is conducted to obtain criteria weights and fuzzy VIKOR is applied to rank the social media platforms. Sudipa et al. (2020) investigate the selection of social media platforms for online businesses with the PROMETHEE II method.

Wu et al. (2020) propose using MCDM methods to select variety shows for television stations based on social media competition. The Fuzzy Delphi method is used to select criteria, DEMATEL is applied to verify interdependencies, ANP is conducted to obtain weights, and for the final step, TOPSIS is utilized to rank the alternatives. Mukul et al. (2019) apply an MCDM approach to evaluate digital marketing technologies. In the study, AHP is applied to determine criteria weights and COPRAS is used to rank digital marketing technologies. Kang and Park (2014) develop a framework to measure customer satisfaction based on customer reviews by applying sentiment analysis and VIKOR. The proposed model is divided into two stages: data collection and preprocessing (text mining and sentiment analysis), and measurement of customer satisfaction (VIKOR).

3. Methodology

The steps of the methodology are as follows:

- Twitter data generated about the selected companies were gathered.
- The criteria were determined based on Twitter metrics of UGC.
- The decision matrix was defined.
- The weights of the criteria were obtained.
- The alternatives (companies) were ranked.

R, the open-source tool, was used to compute MCDM methods, and the codes are provided in the appendix.

3.1. Selection of the Social Media Platform and the Companies

Twitter, a microblogging service, was chosen as the current study's social media platform sample. Twitter plays an essential role for both institutions and individual users. It enables companies to reach out to customers and share information. Individuals or consumers can contact companies and generate content for them (Chu et al., 2016).

For company selection, the BoomSocial platform (Boomsocial, 2018) was used, which is a website that allows various comparisons and reports on social media. Various industries' ranking lists on this platform were examined. Among the shopping industry's companies, three industries, which include two competitors with the highest number of followers, were determined. In the current study, cosmetics, marketplace, and electronic industries were selected and six companies were evaluated. Cosmetics companies run retail stores where they sell cosmetics and personal care products. The marketplace industry consists of e-commerce companies that sell multi-category products exclusively online, whereas the electronic industry involves multi-channel retail chains where electronic or technology products are sold. To protect the anonymity of the selected companies, they are labelled C1, C2, M1, M2, E1, E2 where "C" for cosmetics, "M" for marketplace, and "E" for electronics.

3.2. Data Collection and Twitter Metrics based on UGC

The library called "Tweetinvi" developed for .NET was used to access the tweets created by users about the companies during February 2018. A Windows form application that references this library was developed in the Visual Studio 2015 environment with the C# scripting language. To extract tweets and relevant metrics, company names were searched as keywords. In the data preprocessing stage, tweets from companies' corporate accounts and irrelevant tweets (bots) were cleaned. The number of tweets shared about companies is given in Table 2.

Table 2. The Number of Tweets Shared About Companies[3]

Companies	C1	C2	M1	M2	E1	E2	Total
#Twitter	6,090	1,034	1,319	1,196	1,612	671	11,922

The Twitter metrics based on UGC were calculated by considering tweets generated and shared about companies, the number of retweets that each tweet received, the number of favorites that each tweet received, and the number of followers that each tweet's owner (user) had. As stated in the literature review, sentiment is an important aspect that should be taken into account. It is selected as a metric in several social media studies (Capatina et al., 2018; Cvijikj et al. (2013); Murdough, 2009; Stich et al. 2015). Sentiment analysis was carried out to determine the overriding sentiment of the tweets. The tweets were labelled manually as positive, neutral, or negative by the researchers, and inter-coder reliability was checked.

[3] The data used in this study were collected within the scope of the master's thesis titled "Social Media Mining and an Application" prepared by the corresponding author. The criteria considered in the study are the original values calculated, which have not been used in any previous study.

After obtaining the sentiments of the tweets, the relevant metrics were considered based on the sentiment types. According to the sentiment of each tweet, the number of tweets about the companies, the number of retweets and likes of each tweet, and the number of followers of users who shared these tweets (reach) were calculated. Table 3 lists the criteria and their associated cost or benefit.

Table 3. Criteria Information

	Criteria	Formula	Cost or Benefit
CR1	Positive tweets ratio	(#positive tweets)/ (#total tweets)	Benefit (max)
CR2	Negative tweets ratio	(#negative tweets)/ (#total tweets)	Cost (min)
CR3	Neutral tweets ratio	(#neutral tweets)/ (#total tweets)	Benefit (max)
CR4	Retweets ratio of positive tweets	(#retweets of positive tweets)/ (#retweets of total tweets)	Benefit (max)
CR5	Retweets ratio of negative tweets	(#retweets of negative tweets)/ (#retweets of total tweets)	Cost (min)
CR6	Retweets ratio of neutral tweets	(#retweets of neutral tweets)/ (#retweets of total tweets)	Benefit (max)
CR7	Favorites ratio of positive tweets	(#favourites of positive tweets)/ (#favourites of total tweets)	Benefit (max)
CR8	Favorites ratio of negative tweets	(#favourites of negative tweets)/ (#favourites of total tweets)	Cost (min)
CR9	Favorites ratio of neutral tweets	(#favourites of neutral tweets)/ (#favourites of total tweets)	Benefit (max)
CR10	Reach ratio of positive tweets	(#followers of positive tweets' owners)/ (#followers of all tweets' owners)	Benefit (max)
CR11	Reach ratio of negative tweets	(#followers of negative tweets' owners)/ (#followers of all tweets' owners)	Cost (min)
CR12	Reach ratio of neutral tweets	(#followers of neutral tweets' owners)/ (#followers of all tweets' owners)	Benefit (max)

Retweets and reach (the number of followers of the users that retweet the company's tweets) were decided as criteria based on Malhotra (2012) and Sterne (2010). The cost or benefit of the criteria was defined according to the sentiment types. Negative sentiment states the cost of the criteria, whereas positive sentiment shows the benefit of the criteria. Neutral sentiment is also taken as the benefit of the criteria since sharing, retweeting, and liking tweets that do not involve any negative statements is beneficial to companies' awareness, engagement, and word of mouth (Hoffman & Fodor, 2010). Furthermore, being talked about on social media could be viewed as a strength for companies (Capatina et al., 2018).

CR1, CR2, and CR3 are calculated by dividing the number of positive, negative, and neutral tweets by the total number of tweets. The other criteria, on the other hand deal with the same rate account by considering the number of retweets (CR4, CR5, and CR6), favorites (CR7, CR8, and CR9) and reach (CR10, CR11, and CR12) instead of the number of tweets.

3.3. Data Analysis

The selection of the MCDM methods was made considering both the literature and their applicability. CRITIC, an objective method used for weighting criteria and ARAS and COPRAS, methods to evaluate and rank the performance of decision alternatives, are used in the study.

3.3.1. CRITIC method

The CRITIC method, which was proposed by Diakoulaki et al. (1995), enables to obtain criteria weights objectively in MCDM. The steps of the CRITIC method are given below (Diakoulaki et al., 1995):

Step 1. Defining the decision matrix
For a finite set A of n alternatives and a given f_j system with m evaluation criteria, the problem can be defined in Equation 1:

$$Max\{f_1(a), f_2(a), \dots, f_m(a)/a \in A\} \tag{1}$$

The decision matrix is shown as in Equation 2.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix}_{m\times n} ;\ i = 1, \dots, m;\ j = 1, \dots, n \tag{2}$$

Step 2. Normalizing the decision matrix
An x_j membership function is defined that maps f_j values to the range [0, 1] for each f_j criterion. The x_{aj} value expresses how close the alternative "a" is to the ideal value of f_j^*, and how far it is from the worst performance f_{j^*} value.

$$x_{aj} = \frac{f_j(a) - f_j^*}{f_j^* - f_{j^*}} \tag{3}$$

Afterwards, x_j is obtained and shown in Equation 4.

$$x_j = \left(x_j(1), x_j(2), \dots, x_j(n)\right) \tag{4}$$

Step 3. Defining the correlation matrix
In this step, an $m \times m$ dimension correlation matrix is defined to measure the degree of linear relations between the criteria.

$$\sum_{k=1}^{m}(1 - r_{jk}) \tag{5}$$

Step 4. Calculating the C_j values
The amount of information emitted by the j criterion is calculated using Equation 6, considering both the correlation coefficient and the standard deviation. The greater the value C_j, the more information the corresponding criterion transmits and the greater its relative importance in the decision-making process.

$$C_j = \sigma_j . \sum_{k=1}^{m}(1 - r_{jk}) \tag{6}$$

Step 5. Calculating the criteria weights
In the last step, criteria weights are calculated.

$$w_j = \frac{C_j}{\sum_{k=1}^{m} C_j} \tag{7}$$

3.3.2. ARAS method

ARAS (Additive Ratio Assessment) method, proposed by Zavadskas & Turskis (2010), is an MCDM method that enables the ranking of alternatives and the selection of the best alternative according to the utility function value. The steps of the ARAS method are as follows (Zavadskas & Turskis, 2010):

Step 1. Defining the decision matrix

The decision matrix is shown as in Equation 8, with rows representing alternatives and columns for criteria. The optimum value of the j criterion is denoted by x_{0j}.

$$X = \begin{bmatrix} x_{01} & \cdots & x_{0j} & \cdots & x_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix} \tag{8}$$

The optimal value for each criterion can be calculated as shown in Equations 9 and 10.

$$x_{0j} = \max_i x_{ij}, \quad if \max_i x_{ij} \text{ is preferable} \tag{9}$$

$$x_{0j} = \min_i x_{ij}^*, \quad if \min_i x_{ij}^* \text{ is preferable} \tag{10}$$

Step 2. Normalizing the decision matrix

The dimensions of the criteria in the decision matrix are usually different from each other. To avoid the difficulties caused by this difference, the values of the criteria in the decision matrix should be normalized.

$$\bar{X} = \begin{bmatrix} \bar{x}_{01} & \cdots & \bar{x}_{0j} & \cdots & \bar{x}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{x}_{i1} & \cdots & \bar{x}_{ij} & \cdots & \bar{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{x}_{m1} & \cdots & \bar{x}_{mj} & \cdots & \bar{x}_{mn} \end{bmatrix}; \; i = \overline{0,m}; \; j = \overline{1,n} \tag{11}$$

The criteria with maxima preferable values are normalized as follows:

$$\bar{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \tag{12}$$

The criteria with minima preferable values are normalized by applying the below two-stage procedure:

$$x_{ij} = \frac{1}{x_{ij}^*}; \; \bar{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \tag{13}$$

Step 3. Defining normalized-weighted matrix

The range of values that weights (w_j) can get is denoted by $0 < w_j < 1$ and the sum of criterion weights is expressed by Equation 14.

$$\sum_{j=1}^{n} w_j = 1 \tag{14}$$

Normalized-weighted values are calculated in Equation 15.

$$\hat{x}_{ij} = \bar{x}_{ij}.w_j; \; i = \overline{0,m} \tag{15}$$

The weighted normalization matrix is shown in Equation 16.

$$\hat{X} = \begin{bmatrix} x_{01} & \cdots & x_{0j} & \cdots & x_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix}; \; i = \overline{0,m}; \; j = \overline{1,n} \tag{16}$$

Step 4. Calculating the value of the optimality function

S_i is calculated in Equation 17 to show the optimality function value of ith alternative.

$$S_i = \sum_{j=1}^{n} \hat{x}_{ij}\,;\ i = \overline{0, m} \tag{17}$$

The alternative with the highest value S_i is the best and the one with the least value S_i is the worst.

Step 5. Calculating the utility degree and ranking the alternatives

In this step, the values S_i of the alternatives are compared with the optimality function value of the ideal alternative. The utility degree (K_i) is obtained to the extent that each alternative is similar to the ideal alternative. The calculation is given in Equation 18.

$$K_i = \frac{S_i}{S_0};\ i = \overline{0, m} \tag{18}$$

K_i values are in the range of [0, 1]. The alternative with the highest value K_i is selected as the best alternative.

3.3.3. COPRAS method

COPRAS (COmplex PRoportional ASsessment) method is an MCDM method proposed by Zavadskas et al. (1994). It considers the effects of maximizing the maximum directional criteria and minimizing the minimum directional criteria on the outcome. The steps are listed below (Zavadskas et al., 2004):

Step 1. Defining the decision matrix
The decision matrix is shown as in Equation 19.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix}_{mxn} ;\ i = 1, \dots, m;\ \ j = 1, \dots, n \tag{19}$$

x_{ij} is the element of the decision matrix for i^{th} alternative in j^{th} criteria.

Step 2. Normalizing the decision matrix
The normalization process is conducted using Equation 20.

$$x_{ij}^{*} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}};\ j = 1, \dots, n \tag{20}$$

Step 3. Defining normalized-weighted matrix
Afterwards, the normalized matrix is weighted.

$$\hat{x}_{ij} = x_{ij}^{*}.w_j;\ \ i = 1, \dots, m;\ \ j = 1, \dots, n \tag{21}$$

$$\sum_{j=1}^{n} w_j = 1 \tag{22}$$

Step 4. Calculating the maximizing and minimizing indexes
Index values for S_{+i} maximum oriented and S_{-i} minimum oriented criteria are given in Equations 23 and 24.

$$S_{+i} = \sum_{j=1}^{g} \hat{x}_{ij}\,; \;\; i = 1, \dots, m \tag{23}$$

$$S_{-i} = \sum_{j=g+1}^{n} \hat{x}_{ij}\,; \;\; i = 1, \dots, m \tag{24}$$

Step 5. Calculating the relative weights
Q_i is calculated to express the relative importance value for the alternative i.

$$Q_i = S_{+i} + \frac{\min_i S_{-i} \sum_{i=1}^{m} S_{-i}}{S_{-i} \sum_{i=1}^{m} \frac{\min_i S_{-i}}{S_{-i}}} \tag{25}$$

Step 6. Determining the priority order of alternatives and ranking the alternatives
The degree of utility is calculated as in Equation 26.

$$N_i = \left(\frac{Q_i}{Q_{maks}}\right) x\ 100 \tag{26}$$

The decision alternatives are ranked in descending order of N_i values.

4. Findings

The findings of the study are divided into two sections, the first identifies the criteria weights and the second demonstrates the company rankings.

4.1. Obtaining Criteria Weights

CRITIC method was conducted to obtain criteria weights. The first step, forming the decision matrix, is given in Table 4.

Table 4. The Decision Matrix

Criteria Companies	**CR 1**	**CR 2**	**CR 3**	**CR 4**	**CR 5**	**CR 6**	**CR 7**	**CR 8**	**CR 9**	**CR 10**	**CR 11**	**CR 12**
Cost or Benefit	**max**	**min**	**max**	**max**	**min**	**max**	**max**	**min**	**max**	**max**	**min**	**max**
C1	0.315	0.141	0.544	0.323	0.047	0.630	0.219	0.060	0.722	0.198	0.063	0.739
C2	0.299	0.132	0.569	0.270	0.132	0.598	0.061	0.040	0.899	0.154	0.067	0.779
M1	0.044	0.323	0.633	0.006	0.206	0.788	0.037	0.058	0.906	0.004	0.022	0.974
M2	0.056	0.069	0.875	0.000	0.009	0.991	0.003	0.005	0.992	0.009	0.005	0.986
E1	0.013	0.086	0.901	0.001	0.019	0.979	0.013	0.021	0.966	0.001	0.001	0.998
E2	0.039	0.346	0.615	0.056	0.268	0.677	0.001	0.004	0.995	0.002	0.026	0.972

The weights of the criteria were calculated by following the steps of the CRITIC method in R (see Appendix A) and results are given in Table 5.

Table 5. Criteria Weights

Weights	CR 1	CR 2	CR 3	CR 4	CR 5	CR 6	CR 7	CR 8	CR 9	CR 10	CR 11	CR 12
w_j	0.111	0.034	0.066	0.114	0.035	0.070	0.104	0.069	0.093	0.111	0.090	0.102

The results show that the least important criteria are negative tweets ratio (0.034) and retweets ratio of negative tweets (0.035), whereas positive tweets ratio (0.111), retweets ratio of positive tweets (0.114) and reach ratio of positive tweets (0.111) obtain the highest weights.

4.2. Ranking the Companies

After obtaining weights, companies were ranked by ARAS and COPRAS methods with R codes in Appendix B and Appendix C.

Table 6. Ranking of the Companies

Companies	ARAS		COPRAS	
	Utility Degree (K_i)	Ranking	Priority Order (N_i)	Ranking
C1	0.690	1	1.000	1
C2	0.536	2	0.756	2
M1	0.231	6	0.314	6
M2	0.381	4	0.635	3
E1	0.396	3	0.465	4
E1	0.291	5	0.317	5

As given in Table 6, cosmetics companies ranked first and second for both methods. The only difference between the ranking methods was the ranking of M1 and E1, with one indicating the third rank and the other fourth.

5. Conclusion and Directions for Further Research

Social media is ubiquitous and offers everyone involved unique opportunities. From a business standpoint, companies can benefit from monitoring their customers' digital traces, such as tweets, likes, mentions, blogs, videos, and so on. To comprehend where companies stand on social media is critical. The current study contributes to a growing body of research that focuses on social media studies related to companies and establishes both qualitative and quantitative frameworks for evaluating social media metrics of companies based on brand-related UGC using MCDM methods.

The MCDM approach to social media studies has received little attention in the literature. There are a few studies in the literature that use MCDM methods to rank companies or institutions based on social media (Capatina et al., 2018; Irfan et al., 2018). Furthermore, ranking tools and platforms provide little information about the calculation process, relevant metrics, and their weights. This study proposes an MCDM approach to evaluating companies' social media metrics based on UGC to fill this gap.

This study is the first in two aspects. First, MCDM techniques are recommended to weigh social media metrics and rank companies. Second, brand-related UGC on Twitter is taken into account and criteria are calculated concerning UGC. In addition, the sentiment of the generated contents is an important criterion that should be considered (Capatina et al., 2018; Cvijikj et al., 2013; Hoffman & Fodor, 2010; Murdough, 2009; Stich et al. 2015). In the current study, sentiment analysis was performed and all the metrics of UGC were calculated based on the three sentiment types (positive, neutral, or negative).

The results of the study imply that positive tweets ratio, retweets ratio of positive tweets and reach ratio of positive tweets have the highest weights as criteria for the selected competitors operating in cosmetics, marketplace, and electronics. This finding is reasonable since positive UGC, the retweeting activity of these contents and the reach are critical to the positive image of company's social media performance. In this regard, having an in-depth understanding of the sentiment is crucial for companies and detecting the sentiment of UGC can be viewed as an indicator for social media success. These findings suggest that companies should focus on creating and nurturing an environment for positive UGC, as well as allocating resources to understand the reasons for the sentiment differences.

This study, like any other, has limitations. According to the company rankings, cosmetics companies outperformed electronics and marketplace companies. The reasons for this could be investigated by topic modeling of the tweets. In the current study, only Twitter was used as a data source. Future research might explore UGC on a platform-by-platform basis, considering more social media platforms and several companies. Besides, the industry information that companies operate in can be used to define and weight criteria. Furthermore, the relationship between the social media activity of the companies and their financial success can be examined by including variables from the companies' financial reports in the data set. This could be a fruitful area for further research.

This study conducts an objective MCDM method to obtain weights for the criteria. Future studies may involve subjective or mixed subjective-objective methods. The findings of various MCDM methods can be investigated. More robust results may be obtained by utilizing methods such as COPELAND, which allows a single ranking based on different methods' rankings. In addition, sentiment analysis was performed manually since the irony was detected. For big text data, manual coding cannot be performed effectively and new techniques such as machine learning and deep learning can be conducted for sentiment analysis.

As a final point, it should be noted that R codes in the appendix can provide further implementations for studies involving multiple criteria and alternatives that are difficult to be calculated accurately with spreadsheets. Applying MCDM methods with R codes are recommended as an effective alternative.

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Appendix A: R Codes of CRITIC Method

Note: Packages needed to be installed and called are "readxl" and "matrixStats".

#Step 1: Defining the Decision Matrix

```
#reading excel data:

dataset <- read_excel("C:/xxxxpathxxx/data.xlsx ", col_names = FALSE)

dataset <- as.matrix(dataset)

#giving names to columns and rows:

dimnames(dataset)<-list(Companies=c("C1", "C2", "M1", "M2", "E1", "E2"), Criteria=c("CR1", "CR2", "CR3", "CR4","CR5", "CR6", "CR7", "CR8","CR9", "CR10", "CR11","CR12"))

#assigning the cost or benefit of criteria:

cb <- c("max","min","max","max","min","max","max","min","max","max","min","max")

# obtaining column-based max and min values of xj and their differences:

colmax <- colMaxs(dataset)

colmin <- colMins(dataset)

diff <- colmax-colmin
```

#Step 2: Normalizing the Decision Matrix

```
normmatrix <- matrix(NA, nrow=nrow(dataset), ncol=ncol(dataset))

for (i in 1:ncol(dataset)) {

  for (r in 1:nrow(dataset)) {

    normmatrix[[r,i]] <- ifelse(cb[i]=="max", (dataset[r,i]-colmin[i])/diff[i], (colmax[i]-dataset[r,i])/diff[i])

  }

}
```

#Step 3: Defining the Correlation Matrix

```
#creating the correlation coefficient matrix:

cormatrix <- cor(normmatrix)
```

```
#calculating (1-r_jk):

pcormatrix <- 1-cormatrix
```

#Step 4: Calculating the Cj Values

```
σj <- apply(normmatrix, 2, sd)

cj <- σj*colSums(pcormatrix)
```

#Step 5: Calculating the Criteria Weights

```
wj <- cj/sum(cj)
```

Appendix B: R Codes of ARAS Method

#Step 1: Defining the Decision Matrix

#Optimal value of criterion (x0j) is added to the dataset created in CRITIC codes:

```
dataset_aras <- rbind(xoj=ifelse(cb == "max", colMaxs(dataset), colMins(dataset)), dataset)
```

#Step 2. Normalizing the Decision Matrix

#Before the normalization procedure, cost or benefit transformations are calculated and saved as a new matrix, named cbmatrix:

```
cbmatrix <- matrix(NA,nrow=nrow(dataset_aras),ncol=ncol(dataset_aras))

for (i in 1:ncol(dataset_aras)) {

  for (r in 1:nrow(dataset_aras)) {

    cbmatrix[[r,i]] <- ifelse(cb[i]=="max", dataset_aras[r,i], 1/dataset_aras[r,i])

  }

}

normmatrix_aras <- t(apply(cbmatrix, 1, function(x) x/colSums(cbmatrix)))
```

#Step 3: Defining Normalized-Weighted Matrix

```
wnormmatrix_aras <- t(apply(normmatrix_aras, 1, function(x) x*wj))
```

#Step 4:Calculating the Value of the Optimality Function

```
si <- rowSums(wnormmatrix_aras)
```

Step 5: Calculating the Utility Degree and Ranking the Alternatives

```
ki <- si/si[1]

rank(-ki[-1])
```

Appendix C: R Codes of COPRAS Method

#Step 1: Defining the Decision Matrix

#The same dataset created in CRITIC codes is used since it has the same structure.

#Step 2: Normalizing the Decision Matrix

```
normmatrix_copras <- t(apply(dataset, 1, function(x) x/colSums(dataset)))
```

#Step 3: Defining Normalized-Weighted Matrix

```
wnormmatrix_copras <- t(apply(normmatrix_copras, 1, function(x) x*wj))
```

#Step 4: Calculating the Maximizing and Minimizing Indexes

```
simax <- rowSums(as.matrix(wnormmatrix_copras[,which((cb=="max")==TRUE)]))

simin <- rowSums(as.matrix(wnormmatrix_copras[,which((cb=="min")==TRUE)]))
```

#Step 5: Calculating the Relative Weights

```
#calculating sum of ratio of S-min/S-i-Sum and relative weight (Qi)

ratiosum_minsum <- sum(apply(as.matrix(simin), 1, function(x) min(simin)/x))

Qi <- simax+(min(simin)*sum(simin))/(simin*ratiosum_minsum)
```

#Step 6: Determining the Priority Order of Alternatives and Ranking the Alternatives

```
Ni <- apply(as.matrix(Qi), 1, function(x) x/max(Qi))

rank(-Ni)
```

ETİK VE BİLİMSEL İLKELER SORUMLULUK BEYANI

Bu çalışmanın tüm hazırlanma süreçlerinde etik kurallara ve bilimsel atıf gösterme ilkelerine riayet edildiğini yazarlar beyan eder. Aksi bir durumun tespiti halinde Business, Economics and Management Research Journal'ın hiçbir sorumluluğu olmayıp, tüm sorumluluk makale yazarlarına aittir.

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