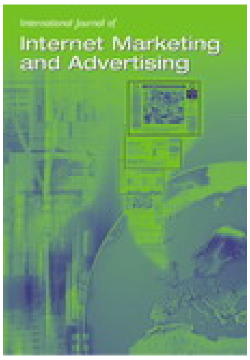


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# Evaluating the impact of emotional advertisement on customers and its relationship with brand value

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# Evaluating the impact of emotional advertisement on customers and its relationship with brand value

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**Abstract:** Emotional advertisement is a style of advertising designed to develop a profound relationship with customers, although it often does not meet the expectations of companies. This inconsistency may indicate that an emotional advertisement damages a company's reputation in social media. Consequently, it is crucial to establish a method for measuring the effect of user response on social influence. This study has two objectives: evaluating emotional advertising and identifying a probable relationship between user response to emotional advertising and the social influence of different firms. After extracting tweets relevant to specific brands, EL2.0 was used to analyse sentiment and emotion. Using regression analysis, the relationship between emotional and sentimental factors and the social influence of the brands was then explored. The results indicate that the valence values of user reaction on Twitter, as an independent variable in the regression model, can appropriately reveal the growth or decline of businesses' social influence.

**Keywords:** advertisement; emotional advertisement; brand value; customer life cycle; advertisement impact; emotional marketing.

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Mohammad Keshavarzian is a graduate student of E-Business at the University of Science and Culture. His research is focused on digital media, consumer behaviour, and how different online advertising strategies affect consumer judgement and decision-making. As the Digital Marketing Manager, he was responsible for creating consumer personas, producing multi-format content, and other types of digital marketing strategies to increase customer awareness and brand reputation.

## 1 Introduction

Consumers expect brands to communicate with them emotionally more than ever before in the digital age. Customer-brand relationships can be strengthened or weakened by different marketing and advertising methods. When consumers are exposed to programmatic marketing, they may feel their privacy is at risk (Núnez-Barriopedro et al., 2022). Presently, some brands utilise social networks for extensive advertising and improved engagement with their users/customers (Castillo-Abdul et al., 2022; Inversini and Sykes, 2013). For many businesses, digital advertisements on social media have become a viable alternative to traditional advertising. Various brands offer contents and adverts to increase client loyalty and interest (Dhaoui and Webster, 2021). Organisations use numerous strategies to develop content and publish adverts, including emotional advertising. This sort of advertising can significantly influence consumers by evoking their emotions (Consoli, 2009). Frequently, this type of advertising involves some sort of emotion (happiness, sadness, excitement, etc.) (Consoli, 2010).

Despite the rapid growth in the use of social networks in recent years, the real impact of this type of advertising remains unclear and some experts believe it can have varying effects on different products. In order for an advertisement to evoke the emotions of consumers, it must be as provocative as possible. On the other hand, exaggeration may have a negative effect on the user. In emotional advertising, it is considered that advertisements that elicit good feelings in consumers will boost brand value and, consequently, brand loyalty.

The impact of a brand on social media indicates the extent to which a person or business can influence others. This influence can be exerted directly or indirectly (Lou and Yuan, 2019; Wang et al., 2019), and it fluctuates throughout time (Meire et al., 2019; Preece et al., 2019). Specifically, this influence may shift as a result of extensive advertising, increased sales, brand value, and other variables (Barreda et al., 2020).

Finding a threshold to solve this contradiction (whether an emotional advertisement has negative or positive effects on users and brand value) can help brands become more conscious of the appropriate application of this advertising style. In the end, this can make them more efficient, allowing them to make fewer errors during the advertising process. The present study attempts to gather more accurate information regarding this paradox by utilising an emotion analysis model (through text mining of actual Twitter user texts), evaluating the efficiency of selected commercials, and comparing the extent of the impact of the advertised brands. This study aims to quantify and assess the actual impact emotional advertising has on consumers. Moreover, it seeks to establish if customer response to an emotional commercial is associated with the growth or decline of a brand's social influence.

## 2 Theoretical background

Different brands primarily use social networks to communicate with and send messages to their customers (Borah et al., 2020; Dhaoui and Webster, 2021). However, the value of brands on social networks varies for several reasons, including customer loyalty and brand activity, (i.e., brand activity on social networks), as well as the creation of diverse and comprehensive advertisements (Cuesta-Valiño et al., 2021; Raza et al., 2018).

Brand value on particular social networks refers to the extent to which brands exert social influence on these networks. There is typically no correlation between the number of a brand's followers on a social network and their engagement with the brand's posts on that network (Chang, 2018). This means that, for example, if a brand has a large number of followers on a social network, it does not necessarily imply that the followers engage with and respond to the brand's posts. Therefore, it is not suggested to determine the value of a brand based just on the number of its social media followers. Often, the brand value on a social network is assessed by analysing and comparing numerous indicators, such as the ratio of likes and other responses to the number of posts a particular brand shares on that social network (Chang, 2018). Higher brand value on social networks helps brands to have a better relationship with their customers, and this can boost the commercial value and sales of brands over time (Achen, 2017; Johnen and Schnittka, 2019).

Recently, a new concept known as emotional advertising has emerged in the field of marketing. This type of advertising seeks to inspire clients to purchase a product or service by appealing to their emotions (Hashem et al., 2020; Lee, 2021). However, this form of promotion does not necessarily result in more sales or a stronger brand-to-customer relationship. In contrast, excessive negative emotions elicited by such commercials could reverse impact and reduce the quality of the brand-to-customer relationship or brand value (Guitart and Stremersch, 2021; Srivastava and Dorsch, 2019). Customers' general feelings can affect their purchasing decisions (Etkin et al., 2018). Previous studies have also researched the effects of brand value on customers' purchases (Hartmann et al., 2021). However, in addition to performing psychological studies, the advertising industry must have a framework for measuring the success or failure of these impacts.

To address this key criterion, Consoli (2010) presents metrics for three ways of emotion display in his study: face, voice, and text. People's emotional state can considerably influence their ultimate purchase decision and their propensity to seek out additional product information. Ghosh and Etkin (Etkin et al., 2018) investigate four cases and conclude, in line with Pocheptsova et al. (2014), that when people are in a positive emotional state, (e.g., joyful or thrilled), they are better able to focus on the crucial qualities of a product or service and make better decisions as a result. Creating positive or negative emotions in individuals is accomplished in various ways. On social media, these emotions might result in the distribution of more content and, consequently, a wider distribution of corporate advertising. Tellis et al. (2019) prove this by analysing the republishing rate of tweets and videos of several brands on Twitter and YouTube.

But it should be borne in mind that according to a study by Meire et al. (2019), arousing emotions in users does not always lead to more responses. Thus, if users experience negative emotions about a particular brand, this brand should empathise with the users and give them information instead of arousing more emotions. Furthermore, it should be noted that identifying the best time and conditions for advertising will directly impact user satisfaction and response. Therefore, if a company's advertising team cannot choose the best time, the user response may be negative (Borah et al., 2020).

The study by Hennig-Thurau et al. (2014) also demonstrates that while positive word-of-mouth (WOM) advertising has minimal effects on users' decisions, negative WOM advertising can completely alter their decisions. Therefore, businesses should prevent unfavourable social media discussions about themselves. In another study, Rocklage and Fazio (2020) examine user reviews of products on the Amazon website and reach intriguing conclusions that are congruent with those of earlier studies. This study demonstrates that, contrary to popular assumption, evaluations that elicit the emotions and sentiments of users do not necessarily result in increased product sales. This occurs because individuals reread reviews of a product or service with their own expectations in mind.

## 3 Literature review and hypotheses development

In general, in some studies, two types of emotional advertising have been considered and examined separately (Srivastava, 2020; Urwin, 2014). Urwin (2014) adds that such advertising may eventually lead to the loss of some clients and make them despise the company, even though it elicits emotions in people. Other research indicates that evoking emotions can increase individuals' desire to shop (Srivastava and Dorsch, 2019; Zhang et al., 2014). These findings are corroborated by Srivastava (2020). Contents that can elicit an emotion in people have the potential to attract their attention more strongly to a brand actively participating in emotional advertising.

Furthermore, such content can ultimately positively affect customers' purchasing decisions. Despite these findings, another study asserts that although emotional advertising can result in increased sales or higher brand awareness in the short-term, its ultimate and long-term effects are uncertain and research findings in this area are equivocal (Niazi et al., 2012; Sandıkcı, 2011). Furthermore, it is often recognised that emotional commercials can also generate positive or negative WOM. Sometimes, even unfavourable online discussion about a brand has a positive effect on its customers. This can improve the possibility that customers will purchase from the same brand (Babić Rosario et al., 2016; Wilson et al., 2017). Emotional advertising is one of the most reliable strategies to elicit an emotional response from clients. In their research project, Brady et al. (2020) also confirm this result. Thus the following hypothesis can be constructed:

H1 Emotional advertisements directly affect a brand's customers and their perceptions of the brand value.

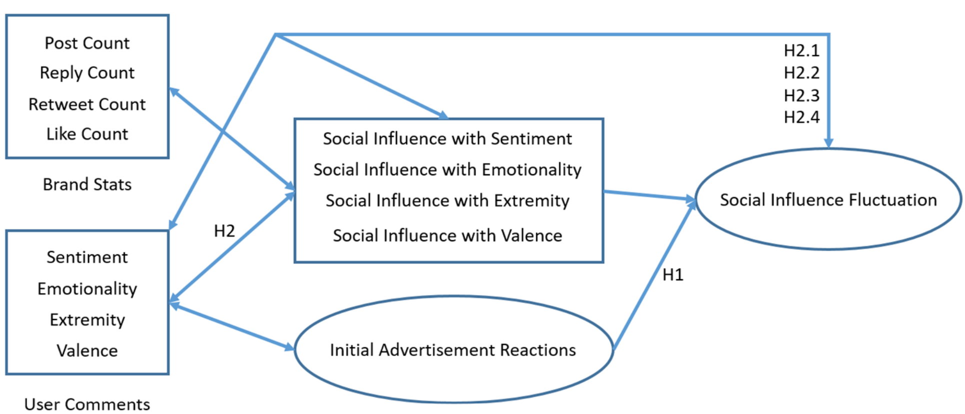
In a related study, Al-Hajjar and Syed (2015) present a novel model for analysing Twitter users' emotional states in technology businesses. Combining emotional analysis with sentiment analysis, they suggest that researchers can utilise these two methodologies together with a greater degree of accuracy (52.6%) than if they were analysed separately, in which case accuracy reduces significantly: Analysis of sentiment (37.3%) and analysis of emotions (39.2%). In a separate study, Dhaoui and Webster (2021) demonstrate that, despite the fact that posting messages can elicit more user reactions, marketers cannot manufacture good responses or conceal bad ones using this method alone (i.e., sharing posts). In an additional investigation, Qaisi and Aljarah (2016) attempted to do sentiment analysis for cloud service providers. First, the tweets from two cloud servers (Azure and AWS) were collected for this purpose. Following this, a simple Bayesian sentiment analysis was performed. Although of interest and significance to the field of emotional advertising, their research is limited to these two Internet service providers, and no comparisons with other providers are conducted. The following hypothesis can be developed:

H2 The emotional variables of consumer reactions to a brand's posts are better suited to measure a brand's social influence than its sentiment on social media.

- H2.1: a strong correlation exists between the emotional variable of consumers' responses to brand posts and the fluctuations in social influence based on the users' *valence* of a brand on a specific social media platform.
- H2.2: a weak correlation exists between the emotional variable of consumers' responses to brand posts and the fluctuations in social influence based on the users' *sentiment* of a brand on a specific social media platform.
- H2.3: a strong correlation exists between the emotional variable of consumers' responses to brand posts and the fluctuations in social influence based on the users' *extremity* of a brand on a specific social media platform.
- H2.4: a strong correlation exists between the emotional variable of consumers' responses to brand posts and the fluctuations in social influence based on the users' *emotionality* of a brand on a specific social media platform.

The literature review in areas pertinent to social media and emotional analysis has been used to develop a theory-based model (Figure 1). The proposed model consists of variables used to determine the social influence of a brand, namely brand stats and user comments, emotional and sentiment analysis variables. The other part is the relation between the initial reactions to an advertisement with the measured social influence and its respective fluctuations.

**Figure 1** Social influence fluctuation relationship with emotional variables framework (see online version for colours)




## 4 Research method

Given the purpose of this study, namely investigating the effects of emotional advertising on the brand value on Twitter, the advertisements referred to as emotional were selected from 12 different brands in different industries. These brands were chosen so that the social influence of each brand may be quantified despite the requirement that they have sufficient Twitter engagement (Chang, 2018). Also, they should have released an advertisement that elicited sufficient emotional responses from enough people (Srivastava and Dorsch, 2019). Finding all emotional advertising that meets the requirements is not possible because it would be tough to select each one.

The authors then created a data scraper to collect all tweets connected to these advertisements and the brands themselves three months before and three months after the advertisements were published. Next, these tweets were normalised and refined so that they were ready to undergo the essential procedures for analysis.

Previous research examined this form of advertising with fewer adverts. Thus the amount of data collected in the present study was sufficient (Hashem et al., 2020; Lalicic et al., 2020). The advertisements with the desired characteristics from the year 2015 onwards were selected. Considerations of practicability led to the conclusion that collecting tweets manually was not a viable option. Similarly, due to their expenses, utilising several APIs was not an acceptable choice. The researchers, therefore, developed a data miner utilising the Python programming language. During the required time period, the miner collected 98,072 tweets, including brand advertisements and people's comments and reactions to these advertisements. This data mining was conducted with a 6-core processor running at 3.6 GHz, 32 MB of cache memory, and 16 GB of RAM.

Twitter provides users with convenient facilities for searching for tweets dealing with specific topics. These facilities were utilised to collect tweets relating directly or indirectly to certain brands three months before and three months after advertisements were published. The reason for choosing this quarterly period was to examine the real impact of these advertisements in a long enough time span. Usually, many studies collect tweets related to a particular brand in a period of only one to seven days.

Since internet dialogues expose the actual effects of advertising over time, the longer the timeframe, the more precise the advertising's impact on brand value (Brady et al., 2020). Similarly, it is widely assumed that shorter time periods do not provide sufficient information about brands and customer responses to perform surveys or write evaluations. As the methodology presented in this study necessitates pre-and post-publication comparisons, the time is split into two three-month segments (Reich et al., 2018; Villarroel Ordenes et al., 2019). As indicated previously, a database including 98072 items was compiled following the collection of all tweets. Nonetheless, this database contains phrases, images, videos, and hashtags associated with the advertising campaigns targeted.

All these tweets needed to be refined so that the remaining ones would contain only usable and categorised texts. As a first phase, EL2.0 software was utilised to measure the consumers' emotional state in relation to the advertisements (Rocklage and Fazio, 2018, 2020; Rocklage et al., 2021b). The brands' tweets were utilised to determine their social influence scores. The procedure which was followed to calculate these points is explained below. However, it should be noted that the tweets written by users within three months prior to and three months after the publication of the specific advertising were included in the calculation procedure. Table 1 display the date the brand's advertisement was released, the number of posts the brand published before and after the commercial, and the number of replies and retweets the brand received before and after the advertisement.

**Table 1** Chosen brands that have published emotional advertisements and their respective statistics

| *Ad brand* | *Advertisement date* | *Advertisement replies* | *Post number before* | *Reply before* | *Retweet before* | *PostNumber after* | *Reply after* | *Retweet after* |
|---|---|---|---|---|---|---|---|---|
| Airbnb | July 4, 2018 | 63 | 129 | 870 | 3,323 | 103 | 1,949 | 7,493 |
| AlwaysLikeAGirl | January 30, 2015 | 37 | 14 | 53 | 337 | 88 | 1,643 | 25,902 |
| BeagleStreet | February 9, 2015 | 45 | 2 | 0 | 26 | 13 | 86 | 126 |
| Budwiser | February 1, 2019 | 88 | 12 | 99 | 49 | 24 | 83 | 228 |
| CathayPacific | January 22, 2015 | 90 | 50 | 85 | 1,003 | 70 | 295 | 2,162 |
| ColdwellBanker | March 28, 2017 | 106 | 330 | 37 | 3,761 | 303 | 195 | 4,165 |
| DoveMen+Care | February 2, 2015 | 80 | 63 | 340 | 2,113 | 61 | 114 | 1,116 |
| Gillette | January 14, 2019 | 274 | 66 | 46,122 | 287,175 | 35 | 43,129 | 284,676 |
| Heineken UK | April 26, 2016 | 120 | 4 | 9 | 123 | 4 | 198 | 4,400 |
| Nike | September 3, 2018 | 217 | 22 | 4,168 | 157,369 | 30 | 4,445 | 81,595 |
| P&G Strong | April 25, 2016 | 68 | 48 | 15 | 85 | 95 | 1,386 | 1,135 |
| P&G The Choice | June 9, 2020 | 14 | 192 | 980 | 1,827 | 284 | 2,538 | 5,432 |
| Tylenol | June 26, 2016 | 54 | 6 | 7 | 40 | 26 | 222 | 1,117 |

The present study employed four control variables for the sentiment-emotional analysis of users' opinions and responses. These variables are as follows:

- Average emotionality valence: the weighted average value of the positive and negative words users include in a text is called its average emotionality valence.
- Average emotionality extremity: the average extent of emotionality valence.
- Emotionality average: positive and negative words indicate the extremity of people's emotions. The average of this extremity is known as the emotionality average.
- Sentiment: different words of a language, regardless of their extremity, are considered to convey feelings according to their positivity or negativity.

The research method necessitated that the average emotionality valence, the average emotionality extremity, and the average emotionality be extracted for each of the adverts as control variables and predictors of regression calculation. According to Rocklage's research, these three variables can be obtained by means of a dictionary (Rocklage et al., 2018). A questionnaire designed by Rocklage is composed of adjectives that respondents react to, or rate, according to their level of emotion. This rating can form a number ranging from 0 (signifying strongly negative) to 9 (meaning strongly positive). The following stage entailed determining the mean of all ratings provided by respondents. This was done to determine the valence and emotional intensity of each word using a dictionary including all the measured factors. The weighted average method was used to obtain each of the three variables for the texts. In keeping with this method, the weighted average of the adjectives available in the EL2.0 dictionary was determined, after which the weight of each adjective was obtained according to the number of times they were used in the texts. User comments on Twitter tend to be short because of the word limit and the social media's characteristics, and EL2.0 was chosen because Evaluative Lexicon focuses on the emotionality of the phrases in a text more than linguistic inquiry and word count 2015 (LIWC) and Warriner wordlist which are popular tools in psychology for quantifying language that tends to show little association with the emotionality of the text (Rocklage et al., 2018).

Focusing on the subject of influence on Twitter, Chang (2018) introduces a model that can measure the strength of individuals or brands on this social network. Numerous categories of information were collected for the present study to quantify the level of an individual's or brand's effect based on this model. Following this, the quality of the posts, i.e., tweets, and the sentiment ratios were computed, which paved the way for the calculation of the degrees of influence. What follows is a presentation of the formulas used to fulfil the requirements mentioned earlier.

Post quality (hereafter referred to as quality) was calculated using the formula below (Chang, 2018):

$$Q(vi) = \log\left(\frac{Forwarded(vi) + Commented(vi)}{Posts(vi)}\right) \tag{1}$$

In this formula, $Q(vi)$ indicates the quality of the posts for the user $vi$. In the numerator, $Forwarded(vi)$ and $Commented(vi)$ respectively represent the number of reposts and the number of comments for each post published by user $vi$. In the denominator, $Posts(vi)$ denote the number of posts published by the user $vi$ in the specified time period. Since the quality of posts, that is, $Q(vi)$, may be very large, the TF-IDF method is used to avoid one-sidedness in the data, and the logarithm function is used at the beginning of the formula.

The sentiment ratio (hereafter referred to as sentiment), in turn, was computed by using the following formula:

$$Sentiment\ Ratio(vi, vj) = \frac{count_{vi,vj}(pos.\ word) + \alpha}{count_{vi,vj}(neg.\ word) + \alpha}$$

$$\{\text{if } sentiment\ ratio(vi, vj) \geq 1, \text{ then positive if } sentiment\ ratio(vi, vj) < 1, \text{ then negative} \tag{2}$$

In the formula above, *vi* is the target user, (i.e., the brand) and *vj* is its follower. First, the number of positive and negative words is counted with reference to the terms introduced in the dictionary; the sentiment is then obtained by dividing them. The smoothing method is used to prevent both the numerator and the denominator of this fraction from becoming 0. Alpha is a fixed number between 0 and 1, which according to Talbot (Talbot et al., 2015), is considered to equal 0.4. If this number is greater than or equal to 1, the outcome of this formula is regarded as positive. Otherwise, it is deemed to be negative. In this study, in addition to considering the positive and negative words, the three variables introduced above were used to calculate the social influence with the sentiment (SIS) such that instead of the sentiment, emotionality valence, emotionality extremity, and user emotionality were taken into account and employed as measures.

Finally, the two formulas above were combined to determine a formula for obtaining the social influence of the specified brands on Twitter (Chang, 2018). Post quality indicates the quantitative part of the formula, and the sentiment ratio is the qualitative part of the formula. This combination is displayed as follows:

$$SIE = \log\left(\frac{Forwarded(vi) + Commented(vi)}{Posts(vi)}\right) \times \sum_{vj}^{n} Emotionality \tag{3}$$

$$SIS = \log\left(\frac{Forwarded(vi) + Commented(vi)}{Posts(vi)}\right) \times \sum_{vj}^{n} Sentiment\ Ratio(vi, vj) \tag{4}$$

$$SIEx = \log\left(\frac{Forwarded(vi) + Commented(vi)}{Posts(vi)}\right) \times \sum_{vj}^{n} Extremity \tag{5}$$

$$SIV = \log\left(\frac{Forwarded(vi) + Commented(vi)}{Posts(vi)}\right) \times \sum_{vj}^{n} Valence \tag{6}$$

After obtaining the SIS for each brand within the specified period before and after publishing advertisements, their growth or decline percentage was determined by comparing their scores. This comparison was conducted to use their differences as an independent variable in the regression model and examine the second research hypothesis of the present study, namely, can emotional advertisements have a relationship with the growth or decline of their influence on Twitter?

Multiple linear regression (MLR) was used to model the relationship between the independent variable (user emotional response to the advertisements) and the dependent variable (SIS growth or decline) (Borah et al., 2020; Rocklage and Luttrell, 2021; Rocklage et al., 2021a).

The MLR operates based on ordinary least squares in which the sum of the squares of the differences between the predicted and observed variables in the study is at a minimum (Arora et al., 2019). If there is a relationship between the two independent variables (social influence of brands) and the predicted values using the non-independent variables (emotional state of user response), their Multiple R in the regression model will be higher than 0 (Hutcheson, 2011; Pohlman and Leitner, 2003). If there is no significant relationship between them, the Multiple R will be closer to 0. Also, if the model used in the regression has a high R square, this model can be employed to predict the dependent variable. Since different possibilities were supposed to be analysed and examined, the adjusted R square was compared with other models. Moreover, to prove the statistical accuracy of the model, an ANOVA test was performed, and its F index was considered (Faraway, 2002; Miller Rupert, 1986).

## 5 Results

Analyses of the emotionality of texts were performed using EL2.0. Through these analyses, the minimums, maximums, averages, and standard deviations of valence, extremity, and emotionality were calculated for each advertisement (ads), the results of which are displayed in Table 1.

Each column in this table represents a calculated variable, with standard deviations serving as the control variables. Furthermore, it should be noted that the averages are used as independent variables for the regression equation. Moreover, each row contains the result of the analysis of the emotionality of user response (users' opinions about and reactions) to the advertisement of the specified brand.

**Table 2** Analysis of emotionality of user response to each brand advertisement

| *Ad brand* | *valence_avg* | *extremity_avg* | *emotionality_avg* | *sentiment_avg* |
|---|---|---|---|---|
| Airbnb | 4.281 | 3.164 | 5.219 | 1.741 |
| AlwaysLikeAGirl | 7.291 | 3.300 | 5.412 | 8.500 |
| BeagleStreet | 7.604 | 3.135 | 5.742 | 3.212 |
| Budwiser | 5.004 | 2.890 | 4.517 | 6.000 |
| CathayPacific | 7.519 | 3.019 | 4.560 | 13.083 |
| ColdwellBanker | 7.161 | 3.104 | 5.620 | 0.588 |
| DoveMen+Care | 7.255 | 3.251 | 5.281 | 5.844 |
| Gillette | 4.215 | 2.887 | 5.071 | 58.500 |
| Heineken UK | 6.838 | 3.198 | 5.149 | 1.421 |
| Nike | 5.159 | 2.886 | 4.728 | 32.429 |
| P&G Strong | 8.163 | 3.663 | 5.757 | 7.176 |
| P&G The Choice | 6.337 | 3.131 | 4.945 | 0.891 |
| Tylenol | 5.787 | 3.180 | 5.427 | 0.843 |

**Table 3** Growth or decline of social influence of brands on Twitter

| *Ad brand* | *SIV(Valence) growth %* | *SIE(Emotionality) growth %* | *SIS(Sentiment) growth %* | *SIEx(Extremity) growth %* |
|---|---|---|---|---|
| Airbnb | 40.729 | 32.987 | 54.179 | 30.339 |
| AlwaysLikeAGirl | 99.675 | 75.682 | 319.166 | 84.201 |
| BeagleStreet | 36.142 | 16.335 | 511.976 | 7.774 |
| Budwiser | 0.579 | 8.951 | 19.579 | 3.100 |
| CathayPacific | 19.758 | 17.577 | 32.712 | 13.681 |
| ColdwellBanker | –11.485 | 20.630 | –61.018 | 4.049 |
| DoveMen+Care | –18.377 | –19.426 | –26.710 | –17.903 |
| Gillette | –31.610 | 9.641 | –79.631 | 3.746 |
| Heineken UK | 77.680 | 119.709 | 19.456 | 97.852 |
| Nike | –12.330 | –7.027 | –16.618 | –7.887 |
| P&G Strong | 307.367 | 290.695 | 62.457 | 305.726 |
| P&G The Choice | 9.081 | 30.113 | –13.822 | 37.296 |
| Tylenol | 88.191 | 84.624 | 21.378 | 82.015 |

Table 2 displays the opinions and responses of users to 13 distinct advertisements published by 12 brands. Each column represents the average of one of the variables analysed and computed using EL 2.0. Ads having a higher average valence, extremity, and emotionality (0–9) elicited greater emotion from users, demonstrating the overall success of the advertisement in relation to the brand's objective. This indicator reveals that of the ads studied, the most significant ones were for the following brands: P&G, Gillette, and Dove.

Collecting brands' tweets before and after they published emotional ads, the researchers collected sufficient information to calculate the brands' social influence by considering the following variables: sentiment, extremity, emotionality, and valence.

Table 3 displays the growth or decline of the social influence of each of the brands in the specified period. These indicators were calculated for each of the four variables stated above.

## 5.1 Hypothesis-testing and regression results

After preparing the data, regression analyses were conducted to establish a relevant relationship between the percentage of growth or reduction in each brand's social influence. These analyses involved calculating the variables mentioned previously, (i.e., sentiment, extremity, emotionality, and valence) within three months after the ads were published.

The regression analyses were performed by considering the variables as independent and dependent regression variables, respectively. This was done in such a way that each emotionality variable was first regarded as a predictor variable. Next, their interaction was taken into account as an independent variable. Finally, higher regression was undertaken using two or three and four predictor variables simultaneously. Tables 4 and 5 show the results of all the tests.

**Table 4** Multiple R for all regression tests (with a confidence interval of 95%)

| *Regression statistics/regression based on* | *Multiple R – SIV (F, significant F)* | *Multiple R – SIEx (F, significant F)* | *Multiple R – SIS (F, significant F)* | *Multiple R – SIE (F, significant F)* |
|---|---|---|---|---|
| Emotionality | 0.508 (3.82, < 0.1) | 0.465 (3.03, <1) | 0.431 (2.51, <1) | 0.477 (3.25, <0.1) |
| Valence | 0.476 (3.22, < 1) | 0.424 (2.41, <1) | 0.403 (2.13, <1) | 0.425 (2.43, <1) |
| Extremity | 0.865 (32.58, < 0.001) | 0.838 (25.86, <0.001) | 0.241 (0.68, <1) | 0.820 (22.65, <0.001) |
| Sentiment | 0.033 (0.01, < 1) | 0.121 (0.16, <1) | 0.350 (1.53, <1) | 0.119 (0.16, <1) |
| Emotionality X Extremity | 0.749 (14.03, < 0.01) | 0.711 (11.21, <0.01) | 0.368 (1.72, <1) | 0.708 (11.06, <0.01) |
| Emotionality X Valence | 0.560 (5.02, < 0.05) | 0.504 (3.75, <0.1) | 0.471 (3.14, <1) | 0.509 (3.84, <0.1) |
| Extremity X Valence | 0.639 (7.61, < 0.05) | 0.594 (6.00, <0.05) | 0.379 (1.85, <1) | 0.589 (5.86. <0.05) |
| Emotionality X Valence X Extremity | 0.682 (9.54, < 0.05) | 0.634 (7.37, <0.05) | 0.428 (2.47, <1) | 0.632 (7.31, <0.05) |
| Emotionality, Extremity | 0.875 (16.31, < 0.001) | 0.854 (13.47, <0.01) | 0.439 (1.20, <1) | 0.831 (11.17, <0.01) |
| Extremity, Valence | 0.872 (15.80, < 0.001) | 0.852 (13.23, <0.01) | 0.404 (0.97, <1) | 0.832 (11.25, <0.01) |
| Emotionality, Valence | 0.574 (2.46, < 1) | 0.520 (1.85, <1) | 0.487 (1.55, <1) | 0.528 (1.94, <1) |
| Emotionality, Valence, Extremity | 0.881 (10.42, < 0.01) | 0.867 (9.08, <0.01) | 0.538 (1.22, <1) | 0.842 (7.30, <0.01) |
| Extremity & Sentiment | 0.865 (14.83, < 0.01) | 0.844 (12.40, <0.01) | 0.428 (1.12, <1) | 0.827 (10.82, <0.01) |
| Emotionality & Sentiment | 0.509 (1.75, < 1) | 0.469 (1.41, <1) | 0.594 (2.73, <1) | 0.481 (1.50, <1) |
| Valence & Sentiment | 0.584 (2.59, < 1) | 0.590 (2.67, <1) | 0.433 (1.15, <1) | 0.590 (2.68, <1) |
| Extremity & Emotionality & Sentiment | 0.876 (9.87, < 0.01) | 0.864 (8.87, <0.01) | 0.607 (1.75, <1) | 0.841 (7.23, <0.01) |
| Extremity & Valence & Sentiment | 0.876 (9.92, < 0.01) | 0.852 (7.94, <0.01) | 0.440 (0.72, <1) | 0.832 (6.75, <0.05) |
| Emotionality & Valence & Sentiment | 0.609 (1.77, < 1) | 0.599 (1.68, <1) | 0.598 (1.67, <1) | 0.603 (1.71, <1) |
| Emotionality & Valence & Extremity & Sentiment | 0.883 (7.08, < 0.01) | 0.868 (6.95, <0.1) | 0.607 (1.17, <1) | 0.843 (4.91, <0.05) |

Multiple R and adjusted R square findings are shown in Tables 3 and 4, respectively, for various tests involving each primary variable as a predictor variable. When both of these indices are closer to 1, the model has a better performance. As evidenced by these tables, emotional advertisements and how the consumers react to an advertisement correlate with the brand value in the given context, which confirms the first hypothesis.

**Table 5** Adjusted R square for all regression tests (with a confidence interval of 95%)

| *Regression statistics/regression based on* | *Adjusted R square – SIV* | *Adjusted R square – SIEx* | *Adjusted R square – SIS* | *Adjusted R square – SIE* |
|---|---|---|---|---|
| Emotionality | 0.190 | 0.145 | 0.112 | 0.158 |
| Valence | 0.156 | 0.105 | 0.086 | 0.106 |
| Extremity | 0.725 | 0.674 | –0.028 | 0.643 |
| Emotionality X Extremity | 0.521 | 0.460 | 0.057 | 0.456 |
| Emotionality X Valence | 0.251 | 0.186 | 0.152 | 0.191 |
| Extremity X Valence | 0.355 | 0.294 | 0.066 | 0.288 |
| Emotionality X Valence X Extremity | 0.416 | 0.347 | 0.109 | 0.345 |
| Emotionality, Extremity | 0.718 | 0.675 | 0.032 | 0.629 |
| Extremity, Valence | 0.712 | 0.671 | –0.005 | 0.631 |
| Emotionality, Valence | 0.195 | 0.124 | 0.084 | 0.135 |
| Emotionality, Valence, Extremity | 0.702 | 0.669 | 0.053 | 0.612 |
| Sentiment | –0.090 | –0.075 | 0.042 | –0.075 |
| Extremity & Sentiment | 0.697 | 0.655 | 0.020 | 0.621 |
| Emotionality & Sentiment | 0.111 | 0.064 | 0.224 | 0.077 |
| Valence & Sentiment | 0.210 | 0.218 | 0.025 | 0.218 |
| Extremity & Emotionality & Sentiment | 0.689 | 0.663 | 0.158 | 0.609 |
| Extremity & Valence & Sentiment | 0.690 | 0.634 | –0.075 | 0.590 |
| Emotionality & Valence & Sentiment | 0.161 | 0.146 | 0.144 | 0.151 |
| Emotionality & Valence & Extremity & Sentiment | 0.669 | 0.629 | 0.053 | 0.566 |

Figures 2 and 3 show the results of all the tests for the variables in question and compare them with each other.

Diagrammatic representations of the data presented in Tables 3 and 4 are presented in Figures 2 and 3. As the tables show, valence, extremity, and emotionality had a better performance than sentiment. The closer the points of the diagrams are to 1, the better the proposed model performs.

As shown in Tables 3 and 4 and Figures 2 and 3, it can be seen that, in all cases, using the three emotional variables to examine the social influence of a brand performed as better predictors than the sentiment variable. The best findings of multiple R in the regression of independent variables and dependent variables in SIV, SIEx, and SIE demonstrate a high correlation between the emotional factors of consumer comments and the fluctuations of the brand's given social influence. Given the table's results and the outcomes, Hypotheses 2.1, 2.3, and 2.4 are accepted.

For the purpose of calculating SIS, only the meaning of the words used by Twitter users and the emotions conveyed by these words were considered, and social influence was calculated using these factors. In this case, considering each emotionality variable did not result in reliable prediction indicators. The highest multiple R value in SIS was computed to be 0.60, and for higher regression, adjusted R square was calculated to be 0.22 at its best state. None of these conditions are sufficiently valid for statistical studies. Hence Hypothesis 2.2 is supported.

**Figure 2** Multiple R diagrams of regression tests (see online version for colours)

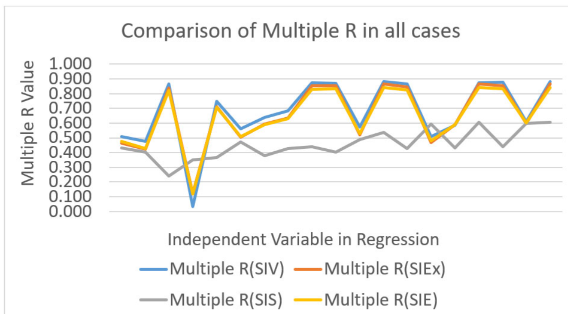
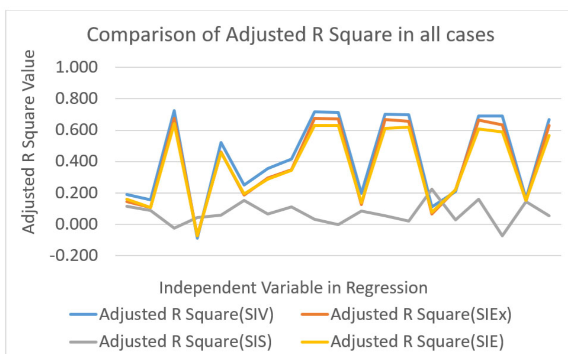



**Figure 3** Adjusted R square diagrams of regression tests (see online version for colours)




On the other hand, better results were obtained when the emotional variables were used to examine social influence. When valence was used as the primary indicator of a brand's social influence (SIV), multiple R values and adjusted R squares produced excellent results for higher regressions. Examining the trend of the lines of the integrated diagrams in Figure 2 shows that, in most cases, the use of emotional variables resulted in better outputs to predict the growth or decline of social influence. These outputs are in such a way that the use of extremity and emotionality gave relatively similar results, with extremity offering a marginally better advantage. The fact that valence operated with a definite advantage over the other two variables is also noteworthy. On the other hand, the regression results indicated that the results obtained were not random and that extremity was highly correlated with social influence based on valence. This proves that emotional variables are a better fit to measure the social influence of a brand on Twitter which correlates with the second hypothesis.

## 6 Conclusions and discussion

### *6.1 Key results of the study*

The present study addressed the issue of how and to what extent the emotional advertising of a brand on Twitter can impact the brand's social influence on this platform. This study was conducted over six months, i.e., three months prior to and three months following the publication of commercials by certain brands. This brief period was selected so that these brands would not launch additional advertising campaigns. The proposed research methodology began with selecting emotional advertisements from twelve distinct brands at different time intervals on Twitter, followed by collecting the necessary data (users' comments and reactions to the advertisements). After data mining and refinement, the data were examined in terms of sentiment and emotionality. In addition, the social influence of the brands on Twitter before and after the commercials were published was measured. Finally, the relationship between user response (users' opinions and responses to advertisements) and the social influence of the companies was investigated.

The results indicated a substantial correlation between user response to a brand's adverts on Twitter and the brand's social influence. To investigate this, the researchers resorted to the OLS regression method. After studying several predictive variables, they determined that the regression model was a suitable response to their analysis. This response was confirmed using an F test; in acceptable cases, significance was proved (that is, $F < 0.01$), and also the coefficient was as follows: $F > 8$. Moreover, in the majority of statistically valid circumstances, the multiple R coefficient was more significant than 0.80.

### *6.2 Theoretical contributions and managerial implications*

This study demonstrates that emotional marketing can correspond with the social influence of businesses in different industries. Previous research has demonstrated that emotional commercials have a powerful impact on brand recall and purchase intent among consumers (Srivastava, 2020). The outcomes of this study expand our knowledge of emotional marketing campaigns, their function on social media platforms, and their potential effects on the company publishing the commercial. Other studies have also indicated that to increase consumer loyalty over the long-term and emotional marketing strategies should emphasise consumer status, aspirations, and needs (Hashem et al., 2020). Brands may leverage their brand image, consumer satisfaction, and consumer happiness to enhance customer loyalty (Cuesta-Valiño et al., 2021). These claims align with the findings of this study since the model used to quantify the social influence of a company includes factors that correspond to social media consumer loyalty. According to previous research, which was also briefly mentioned in the introduction, when users have better communication with brands on social networks and when the social influence of brands on social networks is high, this can have a positive effect on advertising effectiveness and product or service sales. Moreover, organisations that have experienced a growth in social influence have successfully implemented an emotional advertisement that other companies can utilise as a model for improving their own marketing campaigns.

Second, this study presents a novel approach for measuring the influence of social media users based on the emotionality of the respondents' comments. Other research has mostly focused on the attitudes of users to assess their social influence (Chang, 2018) or merely the statistical attributes of each user (e.g., number of followers, retweets, comments) (Chen et al., 2012). They did not find a correlation between the valence derived by evaluating user responses to advertisements published by a specific brand on Twitter and that brand's social influence on Twitter. Despite this lack of convergence, the results of this study are consistent with previous research, and the collected findings clearly indicate the impact of emotional advertising on users and brand value. This model could be utilised by marketers to assess the social influence of enterprises for their reports and to determine whether influencers are worth the budget of their marketing activities.

Lastly, our study presents a pathway for predicting the social influence of companies using the methods available to researchers. Sales and marketing are the primary predictors of business-to-business omnichannel management (Alonso-Garcia et al., 2022). Social media is an integral aspect of marketing strategy, but evaluating the performance of businesses is difficult due to a lack of reliable metrics (Inversini and Sykes, 2013). Thus, creating a foundation for predicting the effects of marketing approaches on social media platforms is significant and facilitates the development of precise models for measuring the effectiveness of marketing campaigns by businesses and researchers.

### *6.3 Limitations and future research*

Future research projects can apply the methodology outlined in this study to evaluate advertisements and their impact on brand memory, social influence, and customers' willingness to purchase products or services on other platforms. This can help to enhance our understanding of the real impact of emotional advertisement on various measures that influence the overall brand value and consumer purchase decisions. Second, examining the influence of advertising in the online space is extremely arduous and misleading; a significant portion of Twitter comments are shared as images and videos. However, it should be underlined that sentiment analysis of social media images and videos can also improve the precision of research results (Kwon et al., 2022). Finally, emotional propaganda can also affect different cultures and sectors (Bou Saada et al., 2022), which can be a research topic for exploration. Differences in cultures and how consumers perceive each brand may lead to new insights regarding whether emotional marketing efforts are always effective in promoting a product or service.

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