# The effect of message repetition on information diffusion on Twitter: An agent-based approach

Manuela López
Marketing Department, University of Murcia, Campus de Espinardo, 30100, Murcia, Spain (email: manuela.lopez@um.es)

Carmen Hidalgo-Alcázar
Departamento de Estudios Económicos, Universidad Miguel Hernández, 03202 Elche, Spain (email: carmen.hidalgoa@umh.es)

Paul Leger
Escuela de Ingeniería, Universidad Católica del Norte, Larrondo 1281, Coquimbo, Chile (email: pleger@ucn.cl)

**This is the accepted version of the article:** López, M., Hidalgo-Alcázar, C., & Leger, P. (2023). The Effect of Message Repetition on Information Diffusion on Twitter: An Agent-Based Approach. *IEEE Transactions on Professional Communication* 66(2), 150-169. DOI: 10.1109/TPC.2023.3260449

## Abstract

**Background:** Twitter offers tools that facilitate the diffusion of information by which companies can engage consumers to share their messages.

**Literature review:** Communication professionals are using platforms such as Twitter to disseminate information; however, the strategies they should use to achieve high information diffusion are not clear. This paper proposes message repetition as a strategy.

**Research questions:** (1) What is the wear-out point of Twitter? (2) How many times should a company repeat a tweet written on its brand page in order to maximize the diffusion for seeds? (3) How many times should a company repeat a tweet written on its brand page to maximize the diffusion while minimizing the number of consumers reaching their wear-out point for seeds? (4) How many times should a company repeat a tweet written on its brand page to maximize the diffusion for non-seeds? (5) How many times should a company repeat a tweet written on its brand page to maximize the diffusion while minimizing the number of consumers reaching their wear-out point for seeds for non-seeds?

**Research methodology:** An agent-based simulation model for information diffusion is proposed as an approach to measure the diffusion of a tweet that has been repeated. The model considers that consumers can reach their wear-out point when they read a tweet several times.

**Results:** The results of the model indicate the number of times a company should send the same tweet in order to achieve high information diffusion before this action has negative effects on consumers. Brand followers are key to achieve high information diffusion; however, consumers begin to feel bothered by the tweet by the sixth repetition.

**Conclusions:** To the best of our knowledge, this is the first study to examine tweet repetition as a strategy to achieve higher information diffusion on Twitter. In addition, it extends the information diffusion literature by controlling the wear-out effect. It contributes to both communication and computational science literature by analyzing a communication problem using an agent-based approach. Finally, the paper contributes to the field of technical professional communication by testing a strategy to reach a great information diffusion, and by creating a tool that any company can use to anticipate the results of a communication campaign created in Twitter before launching it.

**Keywords:**

Agent-Based Model, Information Diffusion, Twitter, Wear-Out Effect

## BACKGROUND

Social network sites (SNSs) allow companies to communicate with consumers [1] at the same time that consumers diffuse information that can be seen by individuals around the world [2]. The diffusion of product-/company-related information between consumers through the Internet is called electronic word-of-mouth (eWOM) [3]. Nearly all information on Twitter is public, and with more than 217 million active users, and more than 500 million tweets sent per day, this SNS has become the most suitable for diffusing information [4]. These disseminated tweets even have a significant effect on other Twitter users, increasing sales [5] and firms' stock returns [6]. Therefore, companies are interested in using SNSs, particularly Twitter, to diffuse information about their products and brands [7]. However, professional communicators and academics alike are still considering the problem of how and what to communicate through these channels in order to achieve high information diffusion [8].

Companies' intentions to engage consumers in sharing company information are called word of mouth (WOM) marketing [9]. Previous studies of WOM marketing campaigns that have the aim of diffusing information have focused on two issues: the type of message that companies should post in order to increase the likelihood of sharing [10], and the type of consumers who have to engage to achieve higher information diffusion [3]. However, the effect of a message's repetition on its diffusion via Twitter is unknown. People cannot read every tweet in their timeline, since previous studies have shown that a tweet has a life of a few hours [11]. Thus, professional communicators could reach different groups of individuals by repeating the same tweet. Many guidelines that offer tips on using Twitter recommend repeating tweets (see, e.g. [12]). Indeed, according to [13], companies repeat their tweets several times. The more times the tweet is sent, the greater the diffusion of that tweet should be. However, the positive effect that the message and its repetition has on consumers could be reduced if consumers see the same message many times [14]. This is because they eventually reach their wear-out point, leading to negative effects toward the product/brand featured in the message. In addition, consumers' negative thoughts and feelings toward the brand could increase [15]. As some consumers can become annoyed by tweet repetition, it is important to identify how to achieve high diffusion using this strategy while avoiding consumers' wear-out point. Thus, this study analyzes the number of times companies should repeat a tweet to achieve the highest information diffusion with the minimum number of consumers reaching their wear-out point.

Information diffusion has been studied on SNSs using traditional methodologies such as statistical modeling [16], [17] and surveys [18]. These methodologies present some issues for studying the diffusion of information. For example, the effects analyzed via statistical modeling could be biased, as they might be affected by variables that are not measured. The method does not enable isolation of the effect of tweet repetition on diffusion, or the extent to which this is affected by individuals who reach their wear-out point. Additionally, studies using statistical modeling methodologies have used the number of times a message has been shared as an indicator of information diffusion (see, e.g. [16]). However, it is important to consider not only the number of times a message has been shared, but also the number of individuals that have seen it. In addition, information diffusion on Twitter has been measured through surveys by assessing retweet intentions (see, e.g. [19]). However, the use of surveys does not enable analysis of the total diffusion of a message in the network. In most cases it is cost prohibitive or not possible to examine these effects on a large scale [20]. In order to overcome these limitations, previous studies have used agent-based models (ABMs) to analyze information diffusion (e.g. [21], [22]). These models allow simple rules of behavior to be described for an individual level, which can then be aggregated to derive conclusions at the overall level [20]. This method has been considered ideally suited for investigating WOM-related marketing problems through the lens of an ABM [20], [23], [24]. The aim is to utilize ABM mainly as a research tool to more deeply understand and examine theoretical and practical communication phenomena. Hence, the aim of this study is to analyze the effect of message repetition via a brand page on the message's diffusion through Twitter, considering consumers' wear-out point. This is achieved via an agent-based simulation approach. Communication professionals can take the study's findings into account when formulating their social media–based communication plans.

The present study makes five specific contributions to the literature. First, it contributes to communication literature by examining tweet repetition as a strategy to achieve higher information diffusion on Twitter. Second, it extends information diffusion literature by controlling the wear-out effect. Third, it adds to literature on how information diffusion can be measured. Fourth, it contributes to both communication and computational science literature by analyzing a communication problem via an agent-based approach. Finally, the paper contributes to technical professional communication literature by testing a strategy by which to reach significant information diffusion, and by creating a tool that any company can use to anticipate the results of a communication campaign created in Twitter before launching it.

This paper is organized as follows. The Literature Review section provides an overview of Twitter, WOM marketing, the wear-out effect, and agent-based simulations. Then, research questions are proposed and the methodology of the study is explained. The results section outlines the results of the simulation. Finally, conclusions and recommendations for further research are presented.

## LITERATURE REVIEW

### *Twitter as a platform to diffuse information: The importance of electronic word-of-mouth*

Twitter has become a powerful communication tool, and has thus received much attention from technical communication scholars. [25] demonstrated how Twitter data and analysis can insightfully inform programmatic decisions. [26] showed the importance of these platforms as a pedagogical tool. [27] examined the use of Twitter for workers as a tool to support their work, while [28] argued that Twitter plays a significant role in gathering, measuring and/or distributing information among technical and professional communicators. In fact, it has been found to be a suitable platform to diffuse information as it allows information to spread more rapidly compared to any other medium [29], [30]. It was successfully used in this manner during the Arab Spring movement [31], the 2012 and 2016 US presidential elections [32], [33], the 2011 Great East Japan earthquake [34], and the Covid-19 pandemic [35]. Additionally, individuals around the world can discuss events and topics on Twitter [36]. This characteristic also makes Twitter a powerful medium for professional communicators to create their social media plans. It is an appropriate means by which to solve reputation crises [37] and to speed up new product adoption [5]. The key to achieving a high diffusion of information via SNSs in general, and in Twitter in particular, is the platform's users. On Twitter, users can share information with each other simply by clicking the "Retweet" button in the tweet.

Twitter may be considered an ideal space for creating eWOM (through clicking "Retweet" in a tweet about a brand) and achieving high information diffusion [38]. Professional communicators can monitor the process of retweeting, and identify not only how many times a given message has been retweeted but also the users who have the highest levels of influence on content diffusion [38]. Tweets can affect company sales [39] and influence consumers' decisions [40]. [39] found that positive eWOM on Twitter increases movie sales, whereas negative eWOM decreases them. Interestingly, [39] found that the strongest effect on movie sales comes from those tweets in which the authors expressed their intention to watch a certain movie. In addition, [41] showed that brand-related tweets allow consumers to access new information about brands, and motivate them to search for additional brand information. Additionally, retweeting can serve as a powerful tool for reinforcing a message [42]. Therefore, companies are interested in engaging consumers to spread the word about their products and brands on Twitter [5]. This study focuses on retweets; thus, we use the definition of transmitted eWOM.

***Word-of-mouth marketing to diffuse information on Twitter***

[9] defined WOM marketing as "the intentional influencing of consumer-to-consumer communications by professional marketing techniques." Basically, the approach consists of disseminating a message to a number of consumers (called *seeds*) in order for them to spread the word. One objective of WOM marketing campaigns is to achieve high diffusion of information about products and brands [38].

Companies can develop WOM marketing strategies on Twitter with the aim of facilitating information diffusion. They can create a profile, known as a brand page, on this platform that consumers can follow [43]. The messages that companies upload onto their brand pages can be seen by their followers, and their followers can transmit this information to their contacts by clicking "Retweet" on the message. The brand followers' contacts who receive the message can then also retweet it, and so on. Via this process, the message can be diffused through Twitter [44]. In this situation, the message of the WOM marketing campaign is conveyed via tweets that the company writes on its brand page, while the seed is composed of the brand page's followers, as they are the initial group of consumers who received the message. These campaigns are very useful for professional communicators in developing their social media plans.

Previous studies of WOM marketing campaigns developed with the aim of achieving high information diffusion have focused on analyzing the type of message that should be sent and the type of seed that should be approached. For example, vivid, interactive, emotional, and surprising messages are more likely to be diffused [10], [45]. Consumers are also more prone to transmit messages that are perceived as useful [46]. On Twitter, messages that include links and hashtags have strong relationships with retweet likelihood [47]. In addition, [48] showed a strong tendency toward transmitting negative tweets in comparison with positive ones. Moreover, [17] showed that emotionally charged Twitter messages are more likely to be retweeted. Regarding the type of seed, previous studies have shown that highly connected consumers are the most suitable seeds to diffuse information, because they have many contacts [3]. Influential information brokers—that is, individuals who connect two otherwise unconnected parts of the network—are also associated with a larger number of retweets for brand content [38]. [43] showed that consumers who retweet brand messages outscore those who do not on brand identification, brand trust, brand community commitment, and membership intention. Additionally, [49] established that individuals are more likely to transmit messages from a trustworthy source, while [50] showed that they are more likely to share information on social media when it was written by individuals who post the same topics. In this vein, [51] demonstrated the power of similarity/homophily in social media. However, another type of strategy could be developed to achieve information diffusion on Twitter. Specifically, companies can send a message to their seeds more than once through this SNS. Indeed, Twitter users may not see all the messages that people they follow write on this SNS [52], meaning that if a company writes a tweet on its brand page, this tweet is not seen by all of its followers. Therefore, companies can repeat the tweet in order for it to be seen by more followers, and in turn increase the likelihood that it will be shared. Message repetition has been extensively studied in traditional media [14]; however, to the best of the authors' knowledge, the effect of message repetition on Twitter is unknown.

***Message repetition and the wear-out effect***

Previous studies have shown that commercial messages have specific effects on consumers. These messages can impact, for instance, consumers' attitude toward the ad or toward the brand, as well as their purchase intention, brand recall, or brand recognition [14], [15]. If a commercial message is repeated, these effects can be higher [53]. Companies contract for many insertions of the same ad on TV and radio, and in newspapers and magazines, in order for consumers be exposed several times to a particular message [14]. However, if the consumer sees the same message too many times, the positive effects could become negative [53]. Two-factor theory provides the theoretical basis for research about repetition effects on message responses [53].

The first phase within two-factor theory is called "wear-in," in which initial exposures to the ad are expected to trigger increasingly positive responses from consumers due to a reduction in uncertainty about the message [53] or an increasing opportunity to learn about the message [54]. In fact, past research has shown the importance of repetition in commercial message effectiveness [55]. When companies repeat a commercial message, it is more likely that consumers will be able to see it. Consumers could even see the same message several times. Multiple exposures to a commercial message increase consumer awareness of the message and facilitate consumer processing of the information included [56]. Purchase intention and attitude toward the brand and toward the message are also positive consequences of message repetition [15].

The second phase is called "wear-out," and starts when the message repetition begins to have adverse effects [57]. Wear-out is when continued repetition results in the onset of tedium, such that the message decreases in effectiveness [14]. When consumers see the same message many times, additional exposures could evoke negative reactions due to boredom, satiation, reactance, and/or tedium, thus leading to them reaching their wear-out point [58]—that is, the number of commercial exposures at which additional exposure has negative effects on consumers [14]. Thus, when a company repeats the same tweet several times, consumers could reach their wear-out point. This could lead to negative consequences for consumers, such as a deterioration of attitudes toward the brand and toward the message [15].

Message repetition has been mainly analyzed with reference to traditional media. According to [59], literature on this topic can be separated into two schools: the minimalists, who posit that a few (one to three) exposures achieve maximum response; and the repetitionists, who believe that repetition (10 to 25 exposures) is necessary for optimal consumer response. Studies about message repetition in online advertising seem to have been inclined toward the minimalist school. For example, [60] showed that after the third exposure to static banners, attitude toward the brand does not increase. In addition, [61] found decreasing returns to clicking after only three ad exposures in a browsing session on a restaurant search website. In fact, media could determine the number of exposures after which consumers reach their wear-out point. Specifically, consumers usually use SNSs to build and maintain social capital [62], so the information that is not oriented to these motivations could be seen as irritating [63]. Such irritation occurs on platforms in which consumers have become used to browsing without having to view advertisements. In fact, previous studies have shown that advertising on an SNS leads to a more negative attitude toward the ad and higher avoidance compared to advertising via traditional media, such as TV or newspapers [64]. However, to the best of our knowledge, the wear-out point on Twitter is unknown.

## RESEARCH QUESTIONS

Based on the literature review, we propose the following research questions (RQs):

**RQ1:** What is the wear-out point of Twitter?

**RQ2:** How many times should a company repeat a tweet written on its brand page in order to maximize the diffusion for seeds?

**RQ3:** How many times should a company repeat a tweet written on its brand page to maximize the diffusion while minimizing the number of consumers reaching their wear-out point for seeds?

**RQ4:** How many times should a company repeat a tweet written on its brand page to maximize the diffusion for non-seeds?

**RQ5:** How many times should a company repeat a tweet written on its brand page to maximize the diffusion while minimizing the number of consumers reaching their wear-out point for seeds for non-seeds?

Our aim is to utilize ABM mainly as a research tool to more deeply understand and examine theoretical and practical marketing phenomena. Thus, the present study uses an ABM simulation to measure the diffusion of a tweet that has been repeated several times.

## RESEARCH METHODOLOGY

As explained in the Literature Review section, to the best of the authors' knowledge accurate information on the Twitter wear-out point is not currently available. Thus, we first developed a study to examine the wear-out point on Twitter. We analyzed the number of tweet repetitions needed to reach consumers' wear-out point. These data are key for the development of the simulation, as they allow us to set a limit beyond which individuals feel annoyed with the brand. Thus, through the simulation, the number of individuals that become annoyed after a specific number of tweet repetitions can be calculated. Additionally, this study enables us to answer RQ1.

***Preliminary study: Wear-out point on Twitter***

*Design*

A 5 (tweet exposures; 1, 2, 3, 4, or 5 exposures) between-subjects experimental study was developed. We followed the minimalist school to design the study. As explained in Literature Review section, previous studies on online advertising have shown that individuals who are exposed to ads in this context reach their wear-out point after a few exposures (e.g. [60]). Thus, we expected the same to occur on Twitter. In this type of experiment, the sample is divided into five groups and each group is exposed to a different stimulus. The difference between stimuli is the manipulated factor—in this case, this is the number of times an individual is exposed to the target tweet. We exposed one group once to the tweet, the next group twice, and so on. The first step to develop the experiment was to design the stimulus.

*Stimuli*

In order to create the stimuli, we first chose the product category and the brand that would send the tweet. We chose wine as the product category for the study. Drinking wine is a subjective, complex, ambiguous experience for many consumers, so companies seek to influence how consumers interpret and value their wine through social media [68]. In addition, social media has been found to be particularly effective among wine consumers [69]. Therefore, we consider wine as a suitable product category for our study. Following previous studies [60], we used a fictitious wine brand, “Bodegas las Condes” in order to avoid brand familiarity.

Then, we created a tweet from the brand (see Figure 1). This tweet was integrated into an image that simulated a Twitter timeline composed of four tweets. The other tweets that comprised the timeline were genuine, in order to create a more realistic scenario. To manipulate the tweet repetition, we created timelines that ensured individuals were exposed to different tweets (including the target tweet, depending on the condition) in all the timelines they saw. Example timelines are shown in Table I.

**Figure 1. Target tweets**


*Procedure*

We conducted an online survey among the target group of the product, which consisted of Twitter users who frequently drink wine. Before answering the questionnaire, individuals were told that they should imagine they were seeing their timeline on Twitter; they then saw one of the timelines created for the study. This process was repeated five times—that is, all individuals saw five Twitter timelines regardless of the condition to which they were assigned. This ensured that the number of timelines seen by the individuals did not affect the results. Individuals in the one-exposure condition saw the target tweet in the fifth timeline, individuals in the two-exposure condition saw the target tweet in the fourth and in the fifth timelines, and so on. The remaining tweets were the same for each condition. For example, all individuals saw the same tweets in the first timeline, except for individuals who were in the five-exposures condition, in which one of the tweets was replaced by the target tweet (see timelines in Table I). The target tweet, shown in Figure 1, was the first shown in the timeline for the five-exposures condition. A summary of the procedure is shown in Figure 2. We followed previous studies in which the message is shown to participants in the same session before answering the questionnaire (see [15], [60]).

**Table I**

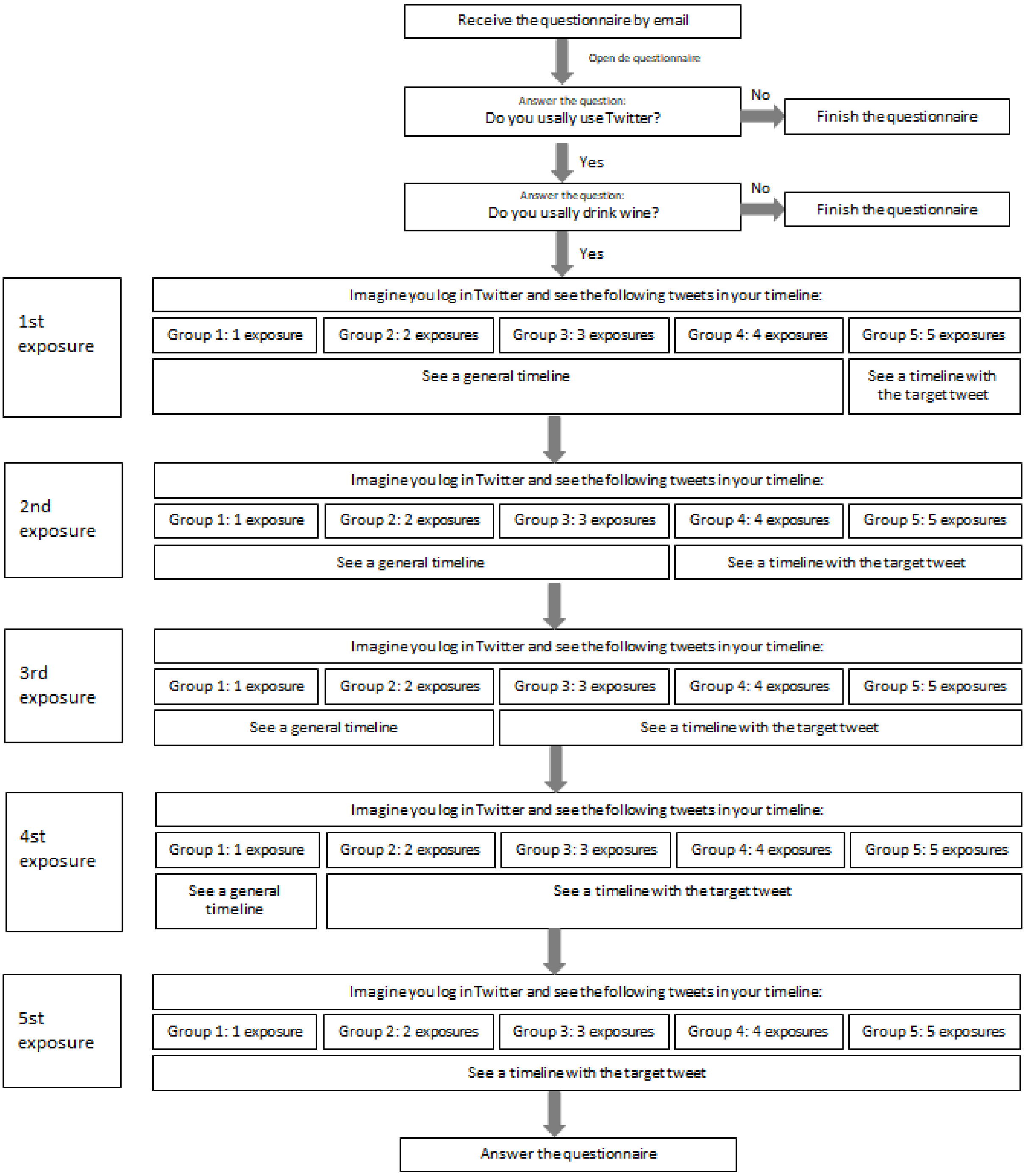
**Example of timelines used in the study**

<table>
<tr><th>First Timeline: Condition one, two, three, and four exposures</th><th>First Timeline: Condition five exposures</th></tr>
<tr><td>


</td><td>


</td></tr>
</table>

**Figure 2. Procedure**




*Measurement*

We followed previous studies that have analyzed the wear-out point mainly via brand attitude as a dependent variable. Thus, we measured brand attitude by using three items based on the scale in [70] (Cronbach's alpha = 0.783). These items were measured using 11-point semantic differential scales. We also asked participants how many times they had seen the target tweet, in order to control the manipulation. Finally, demographics such as sex and age were requested.

*Participants*

Participants were recruited from an online Spanish consumer panel maintained by a market research firm. The panel consists of Internet users who agree to participate periodically in online surveys in exchange for small rewards and gifts. Members of this panel received an email inviting them to participate in the study. Before answering the questionnaire, their consent to participate in the study was requested. We obtained 232 valid questionnaires.

*Results*

The results enable us to answer RQ1 (What is the wear-out point of Twitter?).

The mean age of the sample was 40 years old, and nearly 54.3% of the subjects were male. There were no differences in attitude towards the brand for both genres ($F(230,1)=1.394$, $p > 0.1$) and different ages ($ß = 0.078$, $p > 0.1$). First, we analyzed the manipulation check, which confirmed that individuals remembered approximately how many times they saw the target tweet (see Table II). An analysis of variance (ANOVA) was used to check the wear-out point on Twitter. As Table III shows, tweet repetition had a significant effect on attitude toward the brand ($F(4, 227) = 3.587$, $p < 0.01$). A Scheffe test was also developed to examine the differences between conditions. Results show that there are no significant differences in attitude toward the brand for one- and two-tweet repetitions. However, in the three-tweet repetition condition attitude toward the brand was significantly higher than in the condition in which the tweet was repeated once. Additionally, with four repetitions the attitude was significantly lower than with three repetitions, but was similar to the five-tweet repetition condition.

## Table II

### Manipulation check for tweet repetition

| Condition | Number of Times Individuals Perceived that they had seen the Target Tweet (Mean) | F | p-Value |
|---|---|---|---|
| One tweet exposure | 1.20[a] | | |
| Two tweet exposures | 1.88[b] | | |
| Three tweet exposures | 2.93[c] | 114.671 | 0.000 |
| Four tweet exposures | 3.54[d] | | |
| Five tweet exposures | 4.95[e] | | |

*Note*: Means in the same column with different superscripts differ significantly ($p < .05$) according to the Scheffe test.

## Table III

### Results of the preliminary study

| Condition | Attitude toward the Brand (Mean) | F | p-Value |
|---|---|---|---|
| One tweet exposure | 5.17[a] | | |
| Two tweet exposures | 5.32[ab] | | |
| Three tweet exposures | 6.18[b] | 3.587 | 0.007 |
| Four tweet exposures | 5.15[a] | | |
| Five tweet exposures | 5.25[a] | | |

*Note*: Means in the same column with different superscripts differ significantly ($p < .1$) according to the Scheffe test.

*Conclusions of the preliminary study*

The results show that attitude toward the brand increases until the third exposure to the tweet, after which it decreases. This confirms the existence of a wear-out point on social media, specifically on Twitter. The results also are in line with those of previous studies that have shown that on the Internet, consumers need to experience only a few exposures to commercial information before they become bothered by it (e.g. [60]). We used this result to develop the simulation presented in the next section.

### ***Simulation of information diffusion on Twitter***

*Agent-based model*

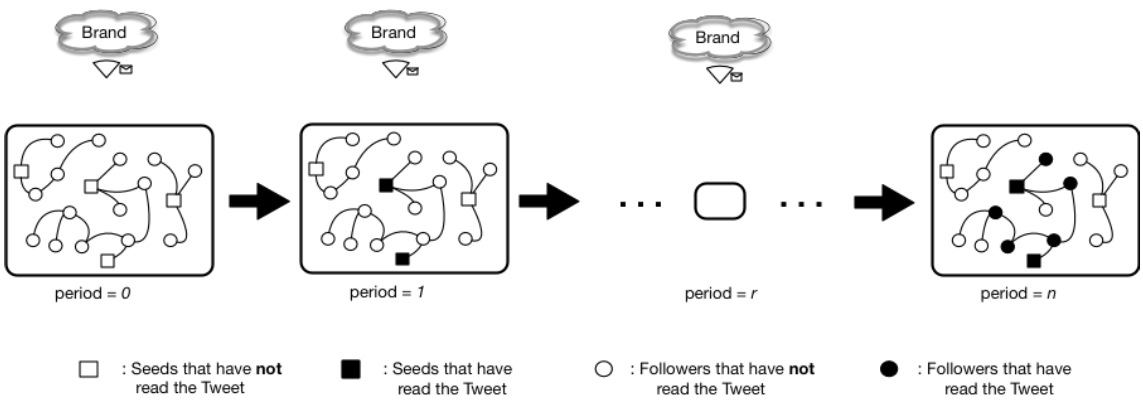
An ABM is a computational model for simulating aggregate consequences based on local interactions among members of a population [21]. ABMs have the potential to become an important market analysis tool in many areas. ABMs have previously been used in marketing studies on cross-market communications [21], simulations of market diffusion of new products [65], examinations of network effects [66], and simulations of new service product diffusion [67]. However, a recent study highlighted that little attention has been paid to ABM applications in the communication literature [23]. The four main components of an ABM are as follows:

- **Environment**: This is the space in which the agents interact [21]. Depending on the scenario, the environment can represent an online network (e.g., SNS, network of email contacts) or an offline network (e.g., neighbors in a city).
- **Agents**: Agents represent individuals, organizations, or any other entity with states and behaviors. These agents vary in their properties and behaviors [20], as well as in the neighbors with whom they interact in the environment.
- **Actions**: Using a set of local rules, agents take actions that potentially affect other agents in each discrete time step [21], [22]. For example, an action could be reading a message on an SNS.
- **Periods:** The duration of an action. Agents can perform an action per period, equivalent to the unit of time stipulated by the model [22].

*ABM for information diffusion on Twitter*

This study develops a simulation of information diffusion on Twitter (SIDT) as a simulation of an ABM that considers the wear-out point of Twitter users. This model will allow us to answer RQ2, 3, and 4. Figure 3 illustrates the evolution in *n* discrete periods of a network when a company sends the same tweet *r* times through its brand account on Twitter. First, the simulation starts when seeds (i.e., followers of the brand page) receive the tweet ($t$ = 0). In period 1, some seeds *may* read this tweet, and those who read the tweet *may retweet* it in the second period. In the next periods of the simulation, the remaining users may read and retweet the tweet. It is worth mentioning that during the first *r* periods the brand page sends the same tweet to its seeds, implying that seeds and other users of the network may reach their wear-out point.

**Figure 3. Evolution of a simulation in SIDT**




For the successful use of SIDT, it must be calibrated with data from the real world. The use of Twitter to diffuse information is especially important for small and medium-sized enterprises (SMEs). The relatively low budget that is needed to develop WOM marketing strategies via SNSs, compared with traditional media such as TV, newspapers, or magazines, makes SNSs an accessible and suitable medium for SMEs. In fact, in a study by [71], 75% of SMEs used social media and 78% of SMEs that used it stated that they saw social media as a critical channel to achieve their business goals. Additionally, among social media platforms many SMEs have stated that they prefer Twitter for developing marketing campaigns [71]. Hence, this study focuses on SMEs. Specifically, to simulate the diffusion of tweets written by a company, the study uses the brand page of a real SME, a Spanish winery that has 23 employees and whose main communication channel is SNSs. *Glass of Bubbly* (https://www.glassofbubbly.com/sww100-leaderboard/) is a premium online magazine on champagne and sparkling wines that awards prizes to the most influential wineries around the world based on their SNS achievements. Out of 200 wineries worldwide the winery used in this study is currently 14th, while it is first among Spain's wineries. Therefore, it is considered a suitable SME for this analysis. The next sections explain our calibration in detail, in particular the environment, periods, agents, and actions.

- ***Environment:*** The environment is represented by a subnetwork of Twitter that represents the universe of users of the target winery. In this subnetwork, the brand page on Twitter has 2,334 seeds (followers), which is the number of followers this winery had when data collection began (March 9, 2016). As the size of the seed in WOM marketing campaigns is usually 5% of the network [22], 46,680 agents (users) are taken to represent the size of this network. Finally, each agent has an average of 208 neighbors, normally distributed, since this number is the average number of followers per Twitter user [72].
- **Periods:** Previous studies have shown that a tweet has a life of a few hours [11]. However, in 2015 Twitter launched an algorithmic timeline called "In case you missed it," where users can see tweets from those they follow that were written at a time they were away, even if this was several hours or days ago. As a consequence, this algorithmic timeline increases tweet life. As users usually log into Twitter at least once a day [73], when a company writes a tweet it can be seen by its followers throughout the day. For this reason, tweet life is considered to be one day, and then each *t* period also corresponds to one day.

- **Agents:** Agents represent Twitter users. A distinction can be made between *seeds* and *non-seeds*. Seeds are the initial group of consumers who receive a tweet; specifically, they are followers of the brand Twitter account. Non-seeds are composed of both seeds' followers and other users of the network (users who do not follow the seed account) who do not follow the brand Twitter account. Each agent can reach different states: (1) the agent did not read the tweet; (2) the agent read the tweet; (3) the agent retweeted the tweet; or (4) the agent reached his/her wear-out point.
- **Actions:** In terms of measuring the effect of tweet repetitions over information diffusion, agents can only do *one of two actions* at each period *t*: *read* or *retweet* a tweet. A user can only read a tweet that was received at period *t-1*, and once the tweet has been read the user can retweet it. A user can only retweet messages to his/her neighbors. Finally, each agent contains two probability values that are normally distributed in all agents of the environment (network): the probabilities of read and retweet.

  A user can read the same tweet many times in different periods. A tweet has a probability $p_r$ of being read at period *t*. The user's probability of reading the tweet depends on the number of times they receive the tweet during the same period *t*. The more times the agent receives the same tweet during that period *t*, the higher their probability of reading it. Then, following previous studies [21], [22], the read probability of agent *i* at period *t* will be 1 minus the probability that the agent does not read the tweet at the *n* times the agent has received the tweet during this period *t* (Equation 1).

  If a tweet is read during period *t*, the agent could retweet it during period *t+1*. There is a retweet probability of $p_{rt}$. The probability of an agent *i* retweeting the tweet will be higher, as this agent receives the tweet more times in the same period *t*. Thus, the retweet probability of agent *i* during period *t* will be 1 minus the probability that the agent does not retweet in this period the tweet that the agent has received *n* times in the previous period (Equation 2). The retweet action depends on the number of times this agent receives the tweet. In SIDT, it is considered that when users reach their wear-out point—that is, when message repetition starts to bother them—they no longer retweet the message. As explained in the preliminary study, SIDT uses three times as the threshold (*w*). Thus, an agent retweets a tweet if the retweet probability is satisfied and the wear-out point is less than threshold *w* (Equation 3). Each agent begins with a wear-out level of 0, and every time a tweet is read the wear-out is increased by 1.

$$P_{ri}\,(t) = 1 - (1 - p_r)^n \quad \textbf{(1)}$$

$$P_{rti}(t) = 1 - (1 - p_{rt})^n \; if\ the\ tweet\ has\ been\ read\ in\ t \quad \textbf{(2)}$$

$$Retweet \begin{cases} Retweet & P_{rt}\ is\ satisfied \cap wear\_out\ point < w \\ No\ retweet & Otherwise \end{cases} \quad \textbf{(3)}$$

Probability values ($p_r$ and $p_{rt}$) were calculated from 135 tweets of the target winery Twitter account written from March 9 to August 22, 2016. The calculation process for the probabilities is explained below.

**Read probability ($p_r$).** Twitter analytics show the number of times a tweet has been read. As each *t* period corresponds to a day, information on each tweet was collected approximately 24 hours after it was written. The read probability ($p_r$) was calculated as the quotient between the number of times a tweet was seen and the number of brand page followers (Equation 4).

**Retweet probability ($p_{rt}$).** Twitter also provides information on the number of times a tweet has been retweeted. Thus, the retweet probability was calculated as the quotient between this information and the number of times that a tweet has been seen (Equation 5).

$$p_r = \frac{Number\ of\ times\ a\ tweet\ has\ been\ seen}{Number\ of\ brand\ page\ followers} \quad \textbf{(4)}$$

$$p_{rt} = \frac{Number\ of\ times\ a\ tweet\ has\ been\ retweeted}{Number\ of\ times\ a\ tweet\ has\ been\ seen} \quad \textbf{(5)}$$

When a simulation is created, each agent uses a normally distributed random value from a range between the mean of each probability +/- its standard deviation.

- **Experiment configuration**

A simulation starts with a group of agents (seeds) who have received the tweet before the first period (*t = 0*). After *n* periods of a simulation, SIDT enables the number of users to have received and read a brand tweet to be determined; this is equivalent to message diffusion. A total of 21 different configurations of simulations were used, where each configuration contained a different tweet repetition—that is, the company was considered to repeat the tweet from 1 to 21 times (*r = 1 to 21*). To prevent stochastic effects of a single run of a simulation, the run of the same configuration of a simulation was repeated at least 30 times (following the practice used in [21]). Finally, each simulation was run with 25 periods because after approximately period 20, no more variations in the simulation were observed. The experiment configuration is summarized in Table IV.

## Table IV

## Summary of the experiment configuration

| Parameters | Value |
|---|---|
| **Network size** | 46,680 agents |
| **Seeds** | 2,334 agents |
| **Followers of Twitter users** | 208 agents |
| **Number of periods** | 25 |
| **Range of read probability of a Tweet ($p_r$)** | [0.100, 0.220] |
| **Range of retweet probability of a Tweet ($p_{rt}$)** | [0.004, 0.012] |
| **Read probability of user *i* at time *t*** | $P_{ri}\,(t) = 1 - (1 - p_r)^n$ |
| **Retweet probability of user *i* at time *t*** | $P_{rti}(t + 1) = 1 - (1 - p_{rt})^n$ |
| **Wear-out point (*w*)** | 3 |
| **Number of repetitions by simulation** | 30 |
| **Number of times that a company sent the tweet (*r*)** | From 1 to 21 |
| **Total number of simulations** | 630 (= 21 * 30) |

SIDT is implemented as a Web application, which is written in JavaScript, a dynamic prototype-based object model with full support for higher-order functions. An Intel Core 2 Duo, 2.93 GHz PC with 4GB of RAM running Windows Server 2012 and Firefox 55.0.3 were used to run the experiment. The time elapsed in the execution of all simulations was 78.2 hours (3.26 days).

For the model, message diffusion is measured as the number of agents (Twitter users) that read the message after *n* periods. In addition, the number of agents who reached their wear-out point and the number of agents who retweeted the message were measured.

## RESULTS

After running the SIDT, an ANOVA was conducted in order to compare the diffusion, wear-out point, and number of retweets reached in each tweet repetition. ANOVA is a statistical test that assesses significant differences in the means of a metric dependent variable for the different groups formed by a categorical variable [74]. The null hypothesis of an ANOVA tests the equivalence of the means of dependent variables between groups using an F-test. A probability is also calculated. That probability allows us to determine how common or rare our F-value is, under the assumption that the null hypothesis is true. If the probability is low enough, we can conclude that our data are inconsistent with the null hypothesis. In this study, the evidence in the sample data is strong enough to reject the null hypothesis for the entire population. This probability is known as the p-value. If the p-value is lower than 0.05 the null hypothesis is rejected, and means are not equal. In contrast, if the p-value is higher than 0.05 the null hypothesis is not rejected, and the means are equal [74]. When the categorical variable has more than three groups, rejection of the null hypotheses means that not all means are equal, so *post hoc* analysis should be developed in order to check differences in means for groups two by two [74]. In this study, the post hoc analysis was developed using the Scheffe test.

The general results can be divided into two: results for seeds, and overall results (the latter of which comprise the results for both seeds and non-seeds). Each are expressed in different ways: results for seeds are depicted as the proportion of seeds who reach a specific state (diffusion; that is, read the tweet, reach wear-out point, or retweet the tweet), while results for the total subnetwork are expressed as the proportion of the total subnetwork who also reach a specific state. These proportions are the means of the variable for all simulations that were run (30 simulations for each tweet repetition). That is, 30 simulations were run in which the tweet was only repeated once, 30 simulations in which the tweet were repeated twice, and so on.

*Results for seeds*

As shown in Table V, there are significant differences in the means of diffusion, the number of seeds who retweeted, and the number of seeds who reached their wear-out point (dependent variables) for the different number of tweet repetitions (categorical variable).

**Table V**

**ANOVA results**

| | Outcome | F(20,609) | Sig. |
|---|---|---|---|
| **Seeds** | Diffusion | 21988.622 | 0.00 |
| | Retweet | 182.377 | 0.00 |
| | Wear-out effect | 16424.455 | 0.00 |
| **Non-seeds** | Diffusion | 140.827 | 0.00 |
| | Retweet | 33.819 | 0.00 |
| | Wear-out effect | 0.900 | 0.59 |
| **Total** | Diffusion | 524.099 | 0.00 |
| | Retweet | 141.716 | 0.00 |
| | Wear-out effect | 16424.452 | 0.00 |

In order to identify in which groups the means are statistically different, we developed Scheffe tests. Table VI shows the results in which means with different superscripts are statistically different from each other. These results allow us to answer RQ2 (How many times should a company repeat a tweet written on its brand page in order to maximize the diffusion for seeds?).

Regarding diffusion, when the tweet is repeated once, it will be diffused among more seeds. However, this only occurs until the 16th repetition, after which the tweet must be repeated twice in order to significantly increase its diffusion. The diffusion slows as the number of tweet repetitions increases. In fact, after the 21st repetition the tweet reaches more than 93% of seeds, while with only four repetitions 50% of seeds have read the tweet at least once. These results allow us to answer RQ3 (How many times should a company repeat a tweet written on its brand page to maximize the diffusion while minimizing the number of consumers reaching their wear-out point for seeds?)

According to the wear-out effect, seeds start to reach their wear-out point at the sixth repetition; 1.5% of seeds reach this point. According to the Scheffe test, the proportion of individuals who reach their wear-out point at the sixth repetition is statistically different than this proportion with one, two, three, four, and five repetitions, where it is not different from zero. From the sixth tweet repetition, the number of seeds who reach the wear-out point increases at each additional repetition. For the 21st repetition, almost half of the population of seeds (44%) will be affected by the wear-out effect. Finally, regarding retweets, the tweet should be repeated three times in order to increase the proportion of individuals who retweet the tweet compared to the first repetition. However, from the 11th repetition the proportion of individuals who retweet increases with four additional repetitions, and until the 13th repetition the number of retweets does not increase.

**Table VI**

**Results for seeds (expressed as proportion of seeds)**

| Tweet Repetition | Diffusion Among Seeds (Proportion of Seeds) | Wear-Out Effect Among Seeds (Proportion of Seeds) | Retweet (Proportion of Seeds) |
|---|---|---|---|
| 1st | .1600$^{a}$ | .0000$^{a}$ | .0012$^{a}$ |
| 2nd | .2958$^{b}$ | .0000$^{a}$ | .0025$^{a}$ |
| 3rd | .4046$^{c}$ | .0001$^{a}$ | .0042$^{ab}$ |
| 4th | .4929$^{d}$ | .0016$^{a}$ | .0059$^{bc}$ |
| 5th | .5632$^{e}$ | .0053$^{ab}$ | .0072$^{bcd}$ |
| 6th | .6257$^{f}$ | .0145$^{b}$ | .0075$^{cd}$ |
| 7th | .6790$^{g}$ | .0271$^{c}$ | .0089$^{de}$ |
| 8th | .7224$^{h}$ | .0416$^{d}$ | .0102$^{def}$ |
| 9th | .7581$^{i}$ | .0638$^{e}$ | .0116$^{efg}$ |
| 10th | .7844$^{j}$ | .0888$^{f}$ | .0124$^{fgh}$ |
| 11th | .8141$^{k}$ | .1161$^{g}$ | .0129$^{fghi}$ |
| 12th | .8334$^{l}$ | .1457$^{h}$ | .0136$^{ghi}$ |
| 13th | .8539$^{m}$ | .1791$^{i}$ | .0158$^{ijk}$ |
| 14th | .8688$^{n}$ | .2102$^{j}$ | .0152$^{hijk}$ |
| 15th | .8818$^{o}$ | .2453$^{k}$ | .0161$^{jkl}$ |
| 16th | .8970$^{p}$ | .2793$^{l}$ | .0167$^{jkl}$ |
| 17th | .9064$^{pq}$ | .3125$^{m}$ | .0174$^{kl}$ |
| 18th | .9149$^{qr}$ | .3479$^{n}$ | .0180$^{kl}$ |
| 19th | .9218$^{rs}$ | .3790$^{o}$ | .0185$^{kl}$ |
| 20th | .9287$^{st}$ | .4126$^{p}$ | .0184$^{kl}$ |
| 21st | .9345$^{t}$ | .4438$^{q}$ | .0192$^{l}$ |

*Note*: Means in the same column with different superscripts differ significantly ($p < 0.05$) according to the Scheffe test.

*Results for total subnetwork*

The total results are expressed as the proportion of all users within the subnetwork who reach a specific state (read the tweet, reach their wear-out point, or retweet the tweet). Total results are also divided into the results for seeds and for non-seeds. As Tables VII–IX show, there are differences between the diffusion, proportion of individuals who reach their wear-out point, and proportion of individuals who retweet the tweet for the different times the tweet is repeated, except for the wear-out effect for non-seeds.

**Table VII**

**Results of diffusion for the entire network and both subnetworks (expressed as a proportion of total network)**

| Tweet Repetition | Total Diffusion (Proportion of Total) | | |
|---|---|---|---|
| | Seeds | Non-Seeds | Total |
| 1st | .0080$^{a}$ | .0025$^{a}$ | .0105$^{a}$ |
| 2nd | .0148$^{b}$ | .0053$^{ab}$ | .0200$^{b}$ |
| 3rd | .0202$^{c}$ | .0082$^{abc}$ | .0284$^{c}$ |
| 4th | .0246$^{d}$ | .0127$^{bcd}$ | .0374$^{d}$ |
| 5th | .0282$^{e}$ | .0151$^{cde}$ | .0433$^{de}$ |
| 6th | .0313$^{f}$ | .0160$^{def}$ | .0473$^{ef}$ |
| 7th | .0340$^{g}$ | .0192$^{defg}$ | .0532$^{fg}$ |
| 8th | .0361$^{h}$ | .0212$^{efgh}$ | .0574$^{gh}$ |
| 9th | .0379$^{i}$ | .0235$^{fgh}$ | .0614$^{hi}$ |
| 10th | .0392$^{j}$ | .0267$^{ghi}$ | .0659$^{ij}$ |
| 11th | .0407$^{k}$ | .0274$^{hi}$ | .0681$^{ijk}$ |
| 12th | .0417$^{l}$ | .0283$^{hi}$ | .0700$^{jkl}$ |
| 13th | .0427$^{m}$ | .0332$^{ijk}$ | .0758$^{klm}$ |
| 14th | .0434$^{n}$ | .0320$^{ijk}$ | .0754$^{klm}$ |
| 15th | .0441$^{o}$ | .0324$^{ijk}$ | .0765$^{lm}$ |
| 16th | .0448$^{p}$ | .0355$^{jk}$ | .0803$^{mn}$ |
| 17th | .0453$^{pq}$ | .0375$^{k}$ | .0829$^{mn}$ |
| 18th | .0457$^{qr}$ | .0363$^{k}$ | .0821$^{mn}$ |
| 19th | .0461$^{rs}$ | .0391$^{k}$ | .0852$^{n}$ |
| 20th | .0464$^{st}$ | .0379$^{k}$ | .0843$^{n}$ |
| 21th | .0467$^{t}$ | .0394$^{k}$ | .0861$^{n}$ |

*Note*: Means in the same column with different superscripts differ significantly ($p < 0.05$) according to the Scheffe test.

## Table VIII

**Results of wear-out effect for the entire network and both subnetworks (expressed as a proportion of the total network)**

| **Tweet Repetition** | **Total Wear-Out Effect (Proportion of Total)** | | |
|---|---|---|---|
| | Seeds | Non-seeds | Total |
| 1st | .0000[a] | 0[a] | .0000[a] |
| 2nd | .0000[a] | 0[a] | .0000[a] |
| 3rd | .0000[a] | 0[a] | .0000[a] |
| 4th | .0001[a] | 0[a] | .0001[a] |
| 5th | .0003[ab] | 0[a] | .0003[ab] |
| 6th | .0007[b] | 0[a] | .0007[b] |
| 7th | .0014[c] | 0[a] | .0014[c] |
| 8th | .0021[d] | 0[a] | .0021[d] |
| 9th | .0032[e] | 0[a] | .0032[e] |
| 10th | .0044[f] | 0[a] | .0044[f] |
| 11th | .0058[g] | 0[a] | .0058[g] |
| 12th | .0073[h] | 0[a] | .0073[h] |
| 13th | .0090[i] | 0[a] | .0090[i] |
| 14th | .0105[j] | 0[a] | .0105[j] |
| 15th | .0123[k] | 0[a] | .0123[k] |
| 16th | .0140[l] | 0[a] | .0140[l] |
| 17th | .0156[m] | 0[a] | .0156[m] |
| 18th | .0174[n] | 0[a] | .0174[n] |
| 19th | .0189[o] | 0[a] | .0189[o] |
| 20th | .0206[p] | 0[a] | .0206[p] |
| 21th | .0222[q] | 0[a] | .0222[q] |

*Note*: Means in the same column with different superscripts differ significantly ($p<0.05$) according to the Scheffe test.

**Table IX**

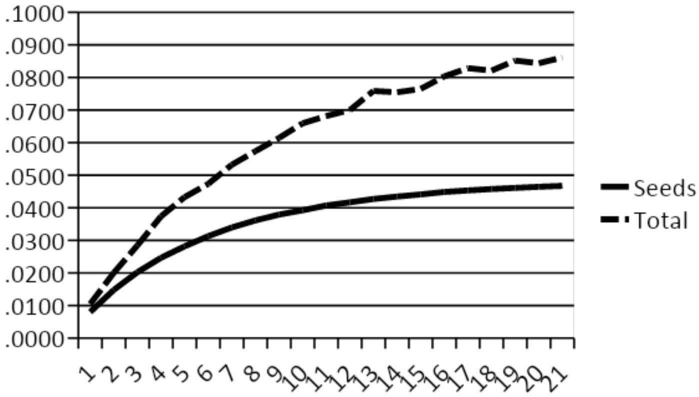
**Results of retweets for the entire network and both subnetworks (expressed as a proportion of the total network)**

| Tweet Repetition | Total Retweet (Proportion of Total) | | |
|---|---|---|---|
| | Seeds | Non-seeds | Total |
| 1st | $.0001^{a}$ | $.0000^{a}$ | $.0001^{a}$ |
| 2nd | $.0001^{a}$ | $.0000^{ab}$ | $.0002^{ab}$ |
| 3rd | $.0002^{ab}$ | $.0001^{abc}$ | $.0003^{abc}$ |
| 4th | $.0003^{bc}$ | $.0001^{abcd}$ | $.0004^{bcd}$ |
| 5th | $.0004^{bcd}$ | $.0001^{abcd}$ | $.0005^{cde}$ |
| 6th | $.0004^{cd}$ | $.0001^{abcde}$ | $.0005^{def}$ |
| 7th | $.0004^{de}$ | $.0002^{bcdef}$ | $.0006^{defg}$ |
| 8th | $.0005^{def}$ | $.0002^{bcdefg}$ | $.0007^{efgh}$ |
| 9th | $.0006^{efg}$ | $.0002^{cdefg}$ | $.0008^{fgh}$ |
| 10th | $.0006^{fgh}$ | $.0002^{defgh}$ | $.0009^{ghi}$ |
| 11th | $.0006^{fghi}$ | $.0002^{defgh}$ | $.0009^{hi}$ |
| 12th | $.0007^{ghi}$ | $.0002^{defgh}$ | $.0009^{hij}$ |
| 13th | $.0008^{ijk}$ | $.0003^{efgh}$ | $.0011^{ijk}$ |
| 14th | $.0008^{hijk}$ | $.0003^{efgh}$ | $.0010^{ijk}$ |
| 15th | $.0008^{jkl}$ | $.0002^{defgh}$ | $.0010^{ijk}$ |
| 16th | $.0008^{jkl}$ | $.0003^{fh}$ | $.0011^{jk}$ |
| 17th | $.0009^{kl}$ | $.0003^{h}$ | $.0012^{k}$ |
| 18th | $.0009^{kl}$ | $.0003^{fgh}$ | $.0012^{k}$ |
| 19th | $.0009^{kl}$ | $.0003^{h}$ | $.0013^{k}$ |
| 20th | $.0009^{kl}$ | $.0003^{fh}$ | $.0012^{k}$ |
| 21th | $.0010^{l}$ | $.0003^{h}$ | $.0013^{k}$ |

Note: Means in the same column with different superscripts differ significantly ($p < 0.05$) according to the Scheffe test.

These results allow us to answer RQ4 (How many times should a company repeat a tweet written on its brand page to maximize the diffusion for non-seeds?). Total diffusion increases as the tweet is repeated an additional time, until the 4th repetition. As can be seen from Table VII, from the 4th to the 10th repetitions the tweet must be repeated twice to significantly increase total diffusion. In addition, from the 16th repetition total diffusion does not increase. If the diffusion for non-seeds is analyzed, four repetitions are needed to reach individuals who are not brand followers. The more times the tweet is repeated, the more repetitions are needed to increase the diffusion for non-seeds. Similar to total diffusion, from the 13th repetition the diffusion does not change; only the diffusion among seeds grows when the tweet is repeated more than 13 times. A comparison between total diffusion and diffusion among seeds can be seen in Figure 4.

**Figure 4. Total diffusion vs. diffusion among seeds**




These results allow us to answer RQ5 (How many times should a company repeat a tweet written on its brand page to maximize the diffusion while minimizing the number of consumers reaching their wear-out point for seeds for non-seeds?). As we can see in Table VIII, according to the wear-out effect, only seeds reach their wear-out point; that is, users who are not followers of the brand page are not affected by the wear-out effect. This result can be seen graphically in Figure 5, where the line that represents the wear-out effect for seeds is superimposed on the total number of individuals who reach their wear-out point.

In relation to the total proportion of individuals who retweet, as shown in Table IX few individuals start to retweet in the first repetition, and the proportion of individuals who retweet does not increase until the tweet is repeated four times. In addition, the majority of retweets are by seeds. In fact, as shown in Figure 6, both lines follow a similar pattern. Non-seeds do not retweet until the 7th repetition, and stop at the 10th repetition; that is, from the 11th to the 21st repetitions the proportion of non-seeds who retweet does not increase significantly.

**Figure 5. Total wear-out effect vs. wear-out effect among seeds**

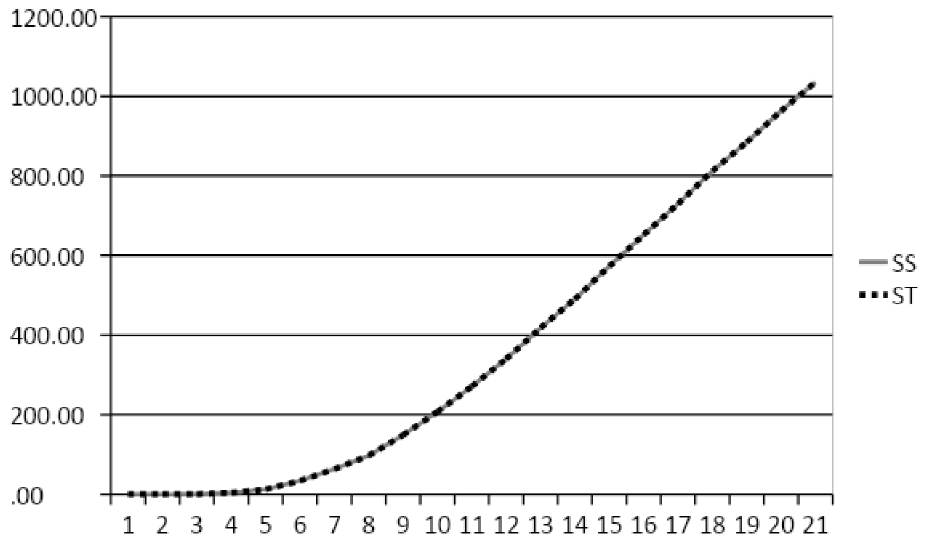
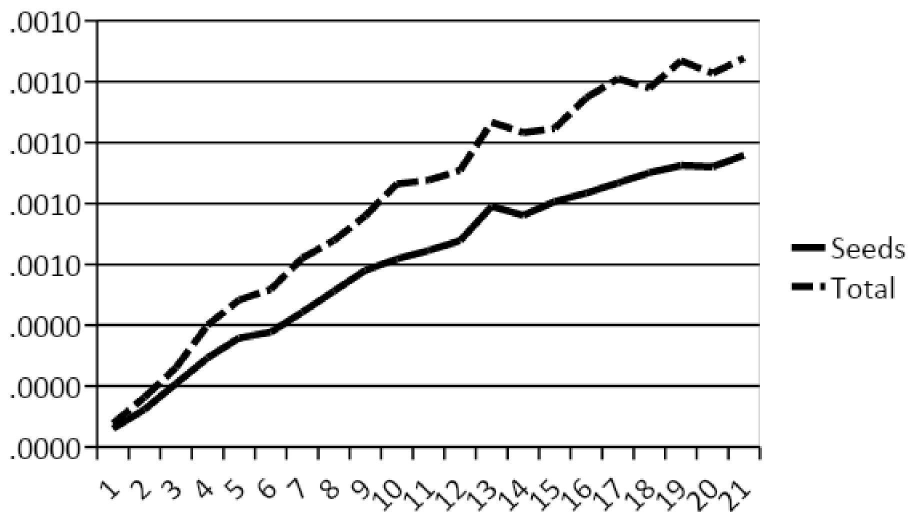



**Figure 6. Total retweets vs. retweets among seeds**




## CONCLUSIONS

SNSs are appropriate platforms for information diffusion [75]; hence, companies create brand pages on such platforms, which allow users to follow these brands. Companies can send messages to their followers, who can easily disseminate them just by clicking "Retweet." However, the question arises as to how many times a company can send the same message through Twitter to reach the highest level of information diffusion on this SNS. In contrast to the general view, if a company sends a tweet many times, this action will not lead to higher diffusion. When consumers see the same tweet several times, they can become annoyed, which has negative effects for the company. Thus, companies should consider the fact that repeating a message could increase information diffusion, but also create a negative effect on consumers.

***Theoretical contributions***

This study contributes to the literature in several ways. First, it extends the WOM marketing literature by studying a new strategy to achieve higher information diffusion on Twitter: tweet repetition. Previous studies have analyzed the characteristics that the tweet should have in order to be highly diffused [47], [48]. Other studies have examined the type of consumers who should be approached to achieve this aim [38], [43]. However, although companies are following this strategy on Twitter [76], to the best of the authors' knowledge the effect of tweet repetition on information diffusion has not been examined to date. This study confirms the effectiveness of this strategy by showing that information diffusion grows until the 16th repetition of the same tweet. However, the growth will slow the more times the tweet is repeated. In fact, total diffusion increases as the tweet is repeated each additional time until the fourth repetition. This paper also analyzed the effects of tweet repetition for seeds and non-seeds. Results show that if the tweet is repeated one more time, it will be diffused more among seeds. Based on the analysis of diffusion for users who are not seeds, four repetitions are needed to reach them. The more times a tweet is repeated, the more repetitions are needed to increase the diffusion for non-seeds. Additionally, seeds are very important for information diffusion, as the majority of retweets are enacted by them. This result is in line with previous studies that showed the importance of brand followers in retweet behavior [43].

Second, this study contributes to the information diffusion literature by controlling the wear-out effect. Previous studies on information diffusion have examined the effect of different strategies to reach the highest diffusion [3], [77]; nevertheless, they have not considered that a high diffusion of information could also lead to negative effects on consumers. This study has shown that only seeds reach their wear-out point; that is, non-followers of the brand page are not affected by the wear-out effect. Seeds started to become bothered by the tweet at the sixth repetition, at which 1.5% of seeds reached their wear-out point. This result is important as it suggests that when a company repeats a tweet several times, it should be careful not to annoy its followers. Brand followers on Twitter can help the company to diffuse information [17], and they can also be used to develop emotional bonds between followers and the brand, such as brand trust, brand attachment, and brand commitment [43]. Thus, companies should not annoy their followers with many tweet repetitions.

Third, this study outlines a method by which to measure information diffusion. Recent research has measured the total diffusion of a message using the number of times the message has been shared [78]. However, not all consumers who have read a message share it; therefore, only assessing the number of times the message has been shared does not lead to knowing the real diffusion of the message. [79] also questioned the use of retweets as a proxy for diffusion, as this measure does not explain all information diffusion on Twitter. Therefore, the current study used the number of individuals who have read the tweet as a more accurate assessment of information diffusion.

Fourth, the study contributes to both communication and computational science literature by analyzing a communication problem with an agent-based approach. ABM is a tool that can help researchers to understand and analyze marketing phenomena that are too complex for conventional analytical or empirical approaches [20]. It is also very suitable for examining WOM marketing campaigns [23]. However, in spite of its advantages, few communication researchers have used it to date.

Finally, the paper contributes to technical professional communication by testing a strategy to reach significant information diffusion, and to create a tool that any company can use to anticipate the result of a communication campaign created in Twitter before launching it. Previous studies about technical communication have shown the power of social media in different fields, such as education [26], and as a tool that supports professional communicators work [27], making programmatic decisions [25], and measuring and diffusing information among technical and professional communicators [28]. In addition, the effect of characteristics of the social media platform (specifically Facebook) on social media engagement has been analyzed [45]. However, strategies to reach significant information diffusion on Twitter have not been studied. This paper outlines a new strategy by which professional communicators can achieve significant information diffusion among their audience on Twitter, and provides guidelines by which to implement the strategy successfully. This strategy could be used to give information not only to consumers but also to individuals in crisis contexts, such as wars or natural disasters, to refute fake news or diffuse information among workers of companies.

***Managerial implications***

The results obtained in this study have several implications for professional communicators. The study's major managerial implication is its presentation of a means by which to measure information diffusion on Twitter by considering the number of repetitions of the message and the wear-out point. The approach is based on the use of ABM, while SIDT is proposed as a tool that companies could use to predict the diffusion of a tweet before implementing a tweet repetition strategy. Companies can easily calculate the probability that a tweet will be read and retweeted by introducing their own Twitter stats (i.e. Twitter analytics that offer information about the number of times a tweet has been seen and retweeted) and their number of followers to the model. Following this process, they would be able to identify the number of times they should repeat a tweet to achieve the highest diffusion while avoiding the user wear-out effect. Currently, companies use Twitter stats to check the success of actions developed on Twitter. Although these stats are an approximation of information diffusion, the number of individuals who have been reached by a tweet is unknown. Twitter stats show the number of tweet displays regardless of whether individuals may have seen the tweet more than once. In addition, by seeing only these stats companies cannot control the negative effect that tweet repetition can create when consumers reach their wear-out point. The current study's results show that companies should repeat the tweet six times in order to achieve the highest information diffusion without bothering seeds. Companies could repeat the same tweet up to 16 times to achieve the highest level of information diffusion; however, they run the risk of annoying their brand followers by doing so.

This paper offers a tool that professional communicators can apply to their specific context or sector before developing a campaign. For example, technical companies could use their Twitter data and apply the model to identify the number of times a tweet should be repeated to reach the highest audience. This will enable them to predict the results of their actions and avoid bothering their audience by repeating the same tweet too many times. In addition, they could program the exact number of times the tweet should be repeated to obtain the best results.

### *Limitations and future research*

Each ABM requires initial information to be appropriately configured. This study was developed using data for a wine company, and the results could vary for different brand pages from different sectors. It would be interesting to replicate the study for brand pages with different characteristics, such as varying sizes or sectors. Specific companies could also use the model with their own data in order to test the results for their individual case.

Additionally, results could vary within the same sector depending on who shares the tweet. Tweet shares using the main brand page of the company could have different results than tweets shared using the Twitter account of a worker, as the number of seeds and the type of account would differ. Thus, future research should analyze differences in diffusion for these two types of Twitter accounts.

Additional studies may also validate the simulation results using, for example, in-depth interviews or experiments. Finally, we only analyzed tweet repetition. Other factors, such as message content or message form, could affect the diffusion of tweets. Therefore, it would be interesting to create a model with these variables to test their effect on the diffusion of a tweet.

***Availability***. SIDT is available online at http://www.absmarketing.cl, where it is possible to test this tool without the need for a browser extension.

## References

[1] Y. Sun, L. Zhai, W. Liu, and K. Yang, "Corporations' Owned Social Media Narrative," *IEEE Transactions on Professional Communication*, vol. 65, no. 2, pp. 280–293, Jun. 2022, doi: 10.1109/TPC.2022.3155917.

[2] M. Ahsan and T. P. Sharma, “Spams classification and their diffusibility prediction on Twitter through sentiment and topic models,” *International Journal of Computers and Applications*, 2020, doi: 10.1080/1206212X.2020.1758430.

[3] O. Hinz, B. Skiera, C. Barrot, and J. U. Becker, “Seeding strategies for viral marketing: An empirical comparison,” *Journal of Marketing*, vol. 75, no. 6, 2011, doi: 10.1509/jm.10.0088.

[4] Twitter, “Company info,” *Twitter*, Jan. 2022. http://twitter.com (accessed Jun. 24, 2022).

[5] T. Hennig-Thurau, C. Wiertz, and F. Feldhaus, “Does Twitter matter? The impact of microblogging word of mouth on consumers’ adoption of new movies,” *J Acad Mark Sci*, vol. 43, no. 3, 2015, doi: 10.1007/s11747-014-0388-3.

[6] J. Xun and B. Guo, “Twitter as customer’s eWOM: an empirical study on their impact on firm financial performance,” *Internet Research*, vol. 27, no. 5, 2017, doi: 10.1108/IntR-07-2016-0223.

[7] N. Mozafari and A. Hamzeh, “An enriched social behavioural information diffusion model in social networks,” *Journal of Information Science*, vol. 41, no. 3, 2015, doi: 10.1177/0165551514565318.

[8] S. Chawla and M. Mehrotra, “Impact of emotions in social media content diffusion,” *Informatica (Slovenia)*, vol. 45, no. 6, 2021, doi: 10.31449/INF.V45I6.3575.

[9] R. v. Kozinets, K. de Valck, A. C. Wojnicki, and S. J. S. Wilner, “Networked narratives: Understanding word-of-mouth marketing in online communities,” *Journal of Marketing*, vol. 74, no. 2, 2010, doi: 10.1509/jmkg.74.2.71.

[10] L. de Vries, S. Gensler, and P. S. H. Leeflang, "Popularity of Brand Posts on Brand Fan Pages: An Investigation of the Effects of Social Media Marketing," *Journal of Interactive Marketing*, vol. 26, no. 2, 2012, doi: 10.1016/j.intmar.2012.01.003.

[11] Sysomos, "REPLIES AND RETWEETS ON TWITTER," *Sysomos*, 2010.

[12] M. McMillan, "Best Practices in Using Twitter for Business," *Business2Community*, 2019. https://www.business2community.com (accessed May 24, 2022).

[13] S. Srivastava, *Digital & Social Media Marketing for MBA*. Agra: Shanti Publications. , 2020.

[14] S. Schmidt and M. Eisend, "Advertising repetition: A meta-analysis on effective frequency in advertising," *Journal of Advertising*, vol. 44, no. 4. 2015. doi: 10.1080/00913367.2015.1018460.

[15] M. C. Campbell and K. L. Keller, "Brand Familiarity and Advertising Repetition Effects," *Journal of Consumer Research*, vol. 30, no. 2, 2003, doi: 10.1086/376800.

[16] R. Huang and X. Sun, "Weibo network, information diffusion and implications for collective action in China," *Information Communication and Society*, vol. 17, no. 1, 2014, doi: 10.1080/1369118X.2013.853817.

[17] S. Stieglitz and L. Dang-Xuan, "Emotions and information diffusion in social media - Sentiment of microblogs and sharing behavior," *Journal of Management Information Systems*, vol. 29, no. 4, 2013, doi: 10.2753/MIS0742-1222290408.

[18] Y. Shan and K. W. King, "The Effects of Interpersonal Tie Strength and Subjective Norms on Consumers' Brand-Related eWOM Referral Intentions,"

*Journal of Interactive Advertising*, vol. 15, no. 1, 2015, doi: 10.1080/15252019.2015.1016636.

[19] S. C. Chu, H. T. Chen, and Y. Sung, “Following brands on twitter: An extension of theory of planned behavior,” *International Journal of Advertising*, vol. 35, no. 3, 2016, doi: 10.1080/02650487.2015.1037708.

[20] W. Rand and R. T. Rust, “Agent-based modeling in marketing: Guidelines for rigor,” *International Journal of Research in Marketing*, vol. 28, no. 3, 2011, doi: 10.1016/j.ijresmar.2011.04.002.

[21] J. Goldenberg, B. Libai, and E. Muller, “Talk of the Network: A Complex Systems Look at the Underlying Process of Word-of-Mouth,” *Marketing Letters*, vol. 12, no. 3, 2001, doi: 10.1023/A:1011122126881.

[22] B. Libai, E. Muller, and R. Peres, “Decomposing the value of word-of-mouth seeding programs: Acceleration versus expansion,” *Journal of Marketing Research*, vol. 50, no. 2, 2013, doi: 10.1509/jmr.11.0305.

[23] M. Chica and W. Rand, “Building agent-based decision support systems for word-of-mouth programs: A freemium application,” *Journal of Marketing Research*, vol. 54, no. 5, 2017, doi: 10.1509/jmr.15.0443.

[24] Y. Zhang, J. Gao, S. Cole, and P. Ricci, “How the Spread of User-Generated Contents (UGC) Shapes International Tourism Distribution: Using Agent-Based Modeling to Inform Strategic UGC Marketing,” *Journal of Travel Research*, vol. 60, no. 7, 2021, doi: 10.1177/0047287520951639.

[25] C. Lam, M. A. Hannah, and E. Friess, “Connecting programmatic research with social media: Using data from Twitter to inform programmatic decisions,” *Special Issue Editors* , vol. 651, 47 , 2008.

[26] S. Vie, “What’s going on?: Challenges and opportunities for social media use in the writing classroom,” *The Journal of Faculty Development*, vol. 29 no. 2, 33–44, 2015.

[27] T. Ferro, and M. Zachry, “Technical communication unbound: Knowledge work, social media, and emergent communicative practices,” *Technical Communication Quarterly*, vol. 23 no. 1, 6–21, 2014.

[28] A. R. Daer, and L. Potts, “Teaching and learning with social media,” *Programmatic Perspectives,* vol. 6 no. 2, 21–40, 2014.

[29] A. Al-Rawi, J. Groshek, and L. Zhang, “What the fake? Assessing the extent of networked political spamming and bots in the propagation of #fakenews on Twitter,” *Online Information Review*, vol. 43, no. 1, 2019, doi: 10.1108/OIR-02-2018-0065.

[30] F. Firdaniza, B. N. Ruchjana, D. Chaerani, and J. Radianti, “Information Diffusion Model in Twitter: A Systematic Literature Review,” *Information (Switzerland)*, vol. 13, no. 1, 2022, doi: 10.3390/info13010013.

[31] A. Hermida, S. C. Lewis, and R. Zamith, “Sourcing the Arab spring: A case study of Andy Carvin’s sources on twitter during the Tunisian and Egyptian revolutions,” *Journal of Computer-Mediated Communication*, vol. 19, no. 3, 2014, doi: 10.1111/jcc4.12074.

[32] H. Wang, D. Can, A. Kazemzadeh, F. Bar, and S. Narayanan, “A System for Real-time Twitter Sentiment Analysis of 2012 U.S. Presidential Election Cycle,” in *Proceedings of the ACL 2012 System Demonstrations*, Jul. 2012, pp. 115–120. [Online]. Available: https://aclanthology.org/P12-3020

[33] L. Potts, and S. Mahnke, "Subverting the platform flexibility of twitter to spread misinformation," in *Platforms, Protests, and the Challenge of Networked Democracy*. Cham: Palgrave Macmillan, 2020, pp. 157–172.

[34] F. Toriumi, T. Sakaki, K. Shinoda, K. Kazama, S. Kurihara, and I. Noda, "Information sharing on twitter during the 2011 catastrophic earthquake," 2013. doi: 10.1145/2487788.2488110.

[35] D. V. B. de Oliveira and U. P. Albuquerque, "Cultural Evolution and Digital Media: Diffusion of Fake News About COVID-19 on Twitter," *SN Computer Science*, vol. 2, no. 6, 2021, doi: 10.1007/s42979-021-00836-w.

[36] J. M. Smith and T. van Ierland, "Framing Controversy on Social Media: #NoDAPL and the Debate about the Dakota Access Pipeline on Twitter," *IEEE Transactions on Professional Communication*, vol. 61, no. 3, 2018, doi: 10.1109/TPC.2018.2833753.

[37] F. Schultz, S. Utz, and A. Göritz, "Is the medium the message? Perceptions of and reactions to crisis communication via twitter, blogs and traditional media," *Public Relations Review*, vol. 37, no. 1, 2011, doi: 10.1016/j.pubrev.2010.12.001.

[38] T. Araujo, P. Neijens, and R. Vliegenthart, "Getting the word out on Twitter: The role of influentials, information brokers and strong ties in building word-of-mouth for brands," *International Journal of Advertising*, vol. 36, no. 3, 2017, doi: 10.1080/02650487.2016.1173765.

[39] H. Rui, Y. Liu, and A. Whinston, "Whose and what chatter matters? the effect of tweets on movie sales," *Decision Support Systems*, vol. 55, no. 4, 2013, doi: 10.1016/j.dss.2012.12.022.

[40] S. A. A. Jin and J. Phua, “Following celebrities’ tweets about brands: The impact of Twitter-based electronic word-of-mouth on consumers source credibility perception, buying intention, and social identification with celebrities,” *Journal of Advertising*, vol. 43, no. 2, 2014, doi: 10.1080/00913367.2013.827606.

[41] J. N. Burkhalter, N. T. Wood, and S. A. Tryce, “Clear, conspicuous, and concise: Disclosures and Twitter word-of-mouth,” *Business Horizons*, vol. 57, no. 3. 2014. doi: 10.1016/j.bushor.2014.02.001.

[42] M. Cha, H. Haddadi, F. Benevenuto, and K. P. Gummadi, “Measuring user influence in twitter: The million follower fallacy,” 2010.

[43] E. Kim, Y. Sung, and H. Kang, “Brand followers’ retweeting behavior on Twitter: How brand relationships influence brand electronic word-of-mouth,” *Computers in Human Behavior*, vol. 37, 2014, doi: 10.1016/j.chb.2014.04.020.

[44] D. Boyd, S. Golder, and G. Lotan, “Tweet, tweet, retweet: Conversational aspects of retweeting on twitter,” 2010. doi: 10.1109/HICSS.2010.412.

[45] M. A. Hannah, and C. Lam, “Drawing from available means: Assessing the rhetorical dimensions of Facebook practice,” *International Journal of Business Communication*, vol. 54 no. 3, 235–257, 2017.

[46] Y. T. Chang, H. Yu, and H. P. Lu, “Persuasive messages, popularity cohesion, and message diffusion in social media marketing,” *Journal of Business Research*, vol. 68, no. 4, 2015, doi: 10.1016/j.jbusres.2014.11.027.

[47] B. Suh, L. Hong, P. Pirolli, and E. H. Chi, “Want to be retweeted? Large scale analytics on factors impacting retweet in twitter network,” 2010. doi: 10.1109/SocialCom.2010.33.

[48] J. Hornik, R. Shaanan Satchi, L. Cesareo, and A. Pastore, “Information dissemination via electronic word-of-mouth: Good news travels fast, bad news

travels faster!," *Computers in Human Behavior*, vol. 45, 2015, doi: 10.1016/j.chb.2014.11.008.

[49] K. Eismann, "Diffusion and persistence of false rumors in social media networks: implications of searchability on rumor self-correction on Twitter," *Journal of Business Economics*, vol. 91, no. 9, 2021, doi: 10.1007/s11573-020-01022-9.

[50] H. Liang, "Decreasing social contagion effects in diffusion cascades: Modeling message spreading on social media," *Telematics and Informatics*, vol. 62, 2021, doi: 10.1016/j.tele.2021.101623.

[51] C. Zhang, C. Zhang, T. Lu, and S. Chen, "Integrating Ego, Homophily, and Structural Factors to Measure User Influence in Online Community," *IEEE Transactions on Professional Communication*, vol. 60, no. 3, 2017, doi: 10.1109/TPC.2017.2703038.

[52] D. Costolo, "Twitter CEO Dick Cistolo, Jack Dorsey interview," *Internatretailer,* 2014. https://www.internetretailer.com (accessed May 09, 2022).

[53] D. E. Berlyne, "Novelty, complexity, and hedonic value. Attention, Perception, & Psychophysics," *Psychonomic Journals*, vol. 8, no. 5A, 1970.

[54] D. J. Stang, "Effects of 'mere exposure' on learning and affect," *Journal of Personality and Social Psychology*, vol. 31, no. 1, 1975, doi: 10.1037/h0076165.

[55] J. Chen, X. Yang, and R. E. Smith, "The effects of creativity on advertising wear-in and wear-out," *J Acad Mark Sci*, vol. 44, no. 3, 2016, doi: 10.1007/s11747-014-0414-5.

[56] P. Vuokko, "The Determinants of Advertising Repetition Effects ," in *Measuring Advertising Effectiveness*, W. D. Wells, Ed. Mahwah, NJ: Erlbaum.: Psychology Press, 1997, pp. 239–260. doi: 10.4324/9781315806099.

[57] C. Pechmann and D. W. Stewart, “Advertising repetition: A critical review of wearin and wearout,” *Current Issues and Research in Advertising*, vol. 11, no. 1–2, 1988, doi: 10.1080/01633392.1988.10504936.

[58] A. Sawyer, “Repetition, Cognitive Responses, and Persuasion ,” in *Cognitive Responses in Persuasion*, R.E. Petty, T.M. Ostrom, and T.C. Brock, Eds. Hillsdale, NJ: Erlbaum., 1981, pp. 237–261.

[59] G. Tellis, *Effective Advertising: Understanding when, how, and why Advertising Works*. 2455 Teller Road, Thousand Oaks California 91320 United States : SAGE Publications, Inc., 2004. doi: 10.4135/9781452229379.

[60] J. Lee, J. H. Ahn, and B. Park, “The effect of repetition in Internet banner ads and the moderating role of animation,” *Computers in Human Behavior*, vol. 46, 2015, doi: 10.1016/j.chb.2015.01.008.

[61] N. S. Sahni, “Effect of temporal spacing between advertising exposures: Evidence from online field experiments,” *Quantitative Marketing and Economics*, vol. 13, no. 3, 2015, doi: 10.1007/s11129-015-9159-9.

[62] P. B. Brandtzæg and J. Heim, “Why people use social networking sites,” in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2009, vol. 5621 LNCS. doi: 10.1007/978-3-642-02774-1_16.

[63] D. G. Taylor, J. E. Lewin, and D. Strutton, “Friends, Fans, and Followers: Do Ads Work on Social Networks?,” *Journal of Advertising Research*, vol. 51, no. 1, 2011, doi: 10.2501/jar-51-1-258-275.

[64] M. J. van der Goot, E. Rozendaal, S. J. Opree, P. E. Ketelaar, and E. G. Smit, “Media generations and their advertising attitudes and avoidance: a six-country

comparison," *International Journal of Advertising*, vol. 37, no. 2, 2018, doi: 10.1080/02650487.2016.1240469.

[65] F. Ma, M. Luo, and H. J. Yang, "Simulation of Market Diffusion of New Product Based on Cellular Automata," in *Global Marketing Conference on Marketing in the Dynamic Global World*, Mar. 2008, pp. 20–23.

[66] J. K. Frels, D. Heisler, J. A. Reggia, and H.-J. Schuetze, "Modeling the Impact of Consumer Interactions in Technology Markets," *J. Cellular Automata*, vol. 1, no. 2, pp. 91–103, 2006, [Online]. Available: http://www.oldcitypublishing.com/JCA/JCAabstracts/JCA1.2abstracts/JCAv1n2p91-103Frels.html

[67] M. Fang, L. Ming, and P. Diyun, "Simulation of New Service Product Diffusion on Cellular Automata," *Journal of Chinese Marketing*, vol. 2, no. 1, pp. 88–94, 2009.

[68] R. Dolan, J. Conduit, C. Frethey-Bentham, J. Fahy, and S. Goodman, "Social media engagement behavior: A framework for engaging customers through social media content," *European Journal of Marketing*, vol. 53, no. 10, 2019, doi: 10.1108/EJM-03-2017-0182.

[69] B. Leigon, "Grape/wine marketing with new media and return of the Boomer," *Practical Winery & Vineyard Journal, (Winter)*, 2011.

[70] G. C. Bruner, "Standardization and justification: Do Aad scales measure up?," *Journal of Current Issues and Research in Advertising*, vol. 20, no. 1, 1998, doi: 10.1080/10641734.1998.10505073.

[71] TheUkDomain, "How small business are using social media," *TheUkDomain*, 2020. https://theukdomain.uk (accessed Jan. 24, 2022).

[72] Expandedramblings, “By the numbers a few amazing Twitter stats,” *Expandedramblings*, 2013. http://expandedramblings.com/ (accessed May 24, 2022).

[73] T. Rosenstiel, J. Sonderman, K. J. Loker, M. Ivancin, and N. Kjarval, “How people use Twitter in general,” *American Press Institute*, 2015. https://www.americanpressinstitute.org (accessed Nov. 19, 2019).

[74] G. R., Iverson, and H. Norpoth, *Analysis of Variance*. Thousand Oaks, CA: Sage Publications, 1987.

[75] E. Bakshy, I. Rosenn, C. Marlow, and L. Adamic, “The role of social networks in information diffusion,” 2012. doi: 10.1145/2187836.2187907.

[76] Wisemetrics, “Should you repeat your tweets? Facts and figures from 1M tweets,” *Wisemetrics*, 2014. http://www.wiselytics.com/ (accessed May 24, 2019).

[77] J. Kwon, I. Han, and B. Kim, “Effects of source influence and peer referrals on information diffusion in Twitter,” in *Industrial Management and Data Systems*, 2017, vol. 117, no. 5. doi: 10.1108/IMDS-07-2016-0290.

[78] M. Zhang, B. J. Jansen, and A. Chowdhury, “Business engagement on Twitter: A path analysis,” *Electronic Markets*, vol. 21, no. 3, 2011, doi: 10.1007/s12525-011-0065-z.

[79] I. Taxidou, P. M. Fischer, T. de Nies, E. Mannens, and R. van de Walle, “Information Diffusion and Provenance of Interactions in Twitter: Is it only about Retweets?,” 2016. doi: 10.1145/2872518.2889393.