ANALYZING SOCIAL INFLUENCE THROUGH SOCIAL MEDIA, A STRUCTURED LITERATURE REVIEW

Remco Snijders, Utrecht University, Department of Information and Computer Science
Remko Helms, Utrecht University, Department of Information and Computer Science

ABSTRACT

The emergence of social media enables billions of people to share their content and in doing so they influence others and are being influenced themselves. This virtual environment provides a new perspective for the current social influence theories. In this study, the state-of-the-art literature on social influence through social media is reviewed. We find that social influence metrics, influence maximization, mobilization, Word-Of-Mouth and Online Reputation Management are important trends in this field of research. Social influence is shown to have a big impact in social media, but the best way to measure, maximize and coordinate this influence is still to be found. Building on the analyzed literature, we present the Online Social Influence Model, which shows the steps that are necessary to manage social influence through social media. The current study can be valuable to both researchers and practitioners, by providing a starting point for further research and identifying opportunities to improve marketing practices.

KEYWORDS

Social Influence, Influence Maximization, Word-Of-Mouth, Social Media

1. INTRODUCTION

The concept of social media, a group of Internet-based applications that allow the creation and exchange of user generated content (Kaplan & Haenlein, 2010), is a popular concept in the realm of Information Systems. Facebook had 1.11 billion monthly active users in March 2013[1], while Twitter had 200 million active users who created 400 million tweets each day in the same month[2]. These numbers show that social media makes user generated content accessible to a huge audience. The explosive growth of this type of media has allowed users to compete for the scarce attention of other users and to influence them by spreading information (Romero, Galuba, Asur & Huberman, 2011). According to Bond et al. (2010), there is increasing interest in the ability to use online social networks to study and influence offline behavior.

Hillman and Trier (2013, p. 3) state that social influence "provides a broad range of concepts to explain how people's individual actions are affected by other people as a result of interaction". This implies that social influence is a natural process, but can be used by people or businesses to change a person's attitude or behavior. Social influence can be used for positive actions (e.g. creating awareness for societal problems, promoting new products) and negative actions (e.g. social hacking, social pressure).

We can distinguish two important types of social influence: normative social influence and informational social influence.

Kelman (1985) is often cited as a fundamental analysis of normative social influence. This type of social influence explains how individuals are influenced, based on norms. Kelman distinguishes three sub-types of normative social influence: compliance, identification and internalization.

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[1] http://investor.fb.com/releasedetail.cfm?ReleaseID=761090, retrieved on May 20th, 2013
[2] https://blog.twitter.com/2013/celebrating-twitter7, retrieved on May 20th, 2013

- *Compliance* occurs when an individual accepts the opinion of others, hoping that this would lead to a favorable reaction of others.
- *Identification* means that an individual accepts the opinion of others to maintain a desired relationship.
- *Internalization* represents the strongest influence and occurs when an individual accepts and beliefs the opinion of others both in public and private.

Informational social influence is explained by Lee, Shi, Cheung, Lim & Sia (2011). This type of social influence involves accepting information or advice from a person who may not have previously been known as a friend or colleague. Informational social influence is especially relevant in the context of social media, in which user-generated content is an important type of information. An example of this type of social influence in social media could be a change in purchasing behavior as a consequence of online customer reviews of a product. These reviews change the attitudes and beliefs of customers and thereby influence behavior.

Social influence theory provides a number of concepts to explain how people's individual actions are affected by other people as a result of interaction (Hillman & Trier, 2013). Hillman and Trier find that social influence theory, known from the real world, is able to explain processes in online social networks. Online social networks contain explicit data on nodes and edges in a social network and thus enable extensive analysis. Therefore, the existence of social influence through social media is a very interesting topic with many opportunities for research.

Recent studies focus on the applicability of fundamental social influence theories in the domain of social media. These studies contribute to both current research and business practices. However, the precise effects and impact of social influence are still difficult to measure and exploit. The popularity of social media and the impact of social influence in these media make this field of research very relevant. Within this field, many different topics are studied and multiple applications are described. An overview of this research and its state-of-art trends would thus be a useful next step. We present a literature review on the current research trends in social influence through social media. The main topics in recent academic literature are outlined and opportunities for further research are identified. We find that research focuses on social influence metrics, influence maximization, mobilization, Word-Of-Mouth and Online Reputation Management. We show that social influence in social media has a significant impact, but the best ways to measure, maximize and coordinate this influence is still to be found. As a contribution to this challenge, we present the Online Social Influence Model, which provides guidance in managing social influence through social media.

This paper is structured as follows. First, section 2 describes the methodology of the literature review. Subsequently, the results in section 3 outline the state-of-art literature in the researched field and guide the creation of the Online Social Influence model. A conclusion of this paper can be found in section 4. Finally, section 5 presents opportunities for further research.

2. METHODOLOGY

The current literature review is conducted using the approach for systematic literature reviews provided by Okoli and Schabram (2010). Okoli and Schabram define a stand-alone literature review as "a journal-length article whose sole purpose is to review the literature in a field, without any primary data collected or analyzed" (p. 2). The authors have written an eight-step guide for writing a stand-alone literature review.

We reviewed recent articles that described social influence through social media, were fundamental for one of those topics or described social influence applications in business. The selection and exclusion process involved a title review, an abstract review and a full screening of the remaining articles. Five relevant articles of the social media track of the European Conference on Information Systems 2013 were included after the selection process, to improve completeness and recentness. By iteratively coding the articles, we came up with the structure of the results section of our paper.

To develop the Online Social Influence Model, we analyzed the different aspects that were coded during the literature review. We combined techniques that were identified in several studies (collecting network data, measuring and maximizing influence) with applications and suggestions that were found (seed exploitation and influencing attitudes). We finally put this in a logical iterative model with a goal and monitoring.

3. RESULTS

The (22) selected articles present a wide variety of qualitative and quantitative work in journals and conferences on information systems, data mining and marketing. In this section, we describe the identified techniques concerning social influence through social media and applications of social influence through social media that are elaborately described in the recent literature.

3.1 Techniques

3.1.1 Measuring Influence

Online social networks enable the analysis of interaction and influence within a network. An important trend in current literature focuses on the actual measurement of online influence. These studies often use Twitter as their data source. Bakshy, Hofman, Mason & Watts (2011) quantify the influence of Twitter users by studying the reposts of their URLs. Reposts differ from retweets in the sense that the original user does not have to be mentioned specifically. With this approach, Bakshy et al. measure the entire diffusion tree of an event and construct a model to predict individual influence.

Other studies measured a Twitter user's influence via number of followers, number of retweets, number of mentions and PageRank (Kwak et al, 2010; Cha et al., 2010; Weng et al., 2010; Ye & Wu, 2010). Cha et al. (2010) find that a high number of followers does not necessarily implicate a high number of retweets and mentions. Weng et al. (2010) propose TwitterRank, an extension of the PageRank algorithm, to measure the topic-sensitive influence of Twitter users. By including topic-sensitivity, the similarity of users can be taken into account and homophily can be studied. The study shows that TwitterRank outperforms other metrics.

Romero et al. (2011) use the concept of passivity in fabricating a model for influence and create an algorithm to quantify the influence of users in a Twitter network. According to the authors, passivity provides a barrier to propagation in a network. The concept is measured using a user retweeting rate and an audience retweeting rate. They show that the correlation between popularity (number of followers) and influence is weaker than might be expected, while passivity is an important factor. Table 1 shows the literature coverage of the different social influence metrics on Twitter.

Table 1. Literature on the variety of social influence metrics on Twitter.

Study / Metric	#followers/ indegree	#retweets	#URL reposts	#mentions/ replies	PageRank	TwitterRank
Bakshy et al. (2011)			X			
Cha et al. (2010)	X	X		X		
Kwak et al. (2010)	X	X			X	
Romero et al. (2011)		X				
Weng et al. (2010)	X				X	X
Ye & Wu (2010)	X	X		X		

Multiple studies have shown that the number of followers is not the best metric for social influence on Twitter. However, the developed algorithms still have room for improvement. This is partly due to the fact that the functioning of social influence (and the role of homophily therein) is not completely understood. Since most research outlines metrics for Twitter, metrics that can be used across different social networks should be topic of further research. Examples of these metrics are network centrality and passivity.

3.1.2 Influence maximization

The influence maximization problem is mentioned in multiple studies and describes the task of influencing a maximum number of nodes in a social network by finding the right seed nodes (Kempe, Kleinberg & Tardos, 2003). Kempe et al. developed a computational algorithm to achieve influence maximization. This algorithm is inspired by the problem in which a product should be marketed in such a way that a small set of

influentials is targeted, but a large set in a network is reached. It is supposed that data on the influence of the individuals is available. Their algorithm includes the existence of different marketing activities, a node's probability of activation, distance centrality and the weight of nodes (which determines how important the activation of a specific node is). Chen, Wang and Wang (2010) build on the work of Kempe et al. by improving the scalability of the algorithm in their own heuristic. They demonstrate that their heuristic is the best for large-scale (online) networks, which enables viral marketing activities in such networks.

Mochalova and Nanopoulos (2013) examine several centrality scores (degree, betweenness, closeness and eigenvector) in social networks and their performance in relation to the seed selection problem. The authors use Facebook data to create a network structure. Based on their experimental results, the authors conclude that the diffusion of information is dependent on the centrality of seed members and the attitude of all other network members. With this knowledge, it is possible to understand in which cases information will or will not spread. The findings can be used to coordinate or characterize the diffusion of information.

Goyal, Bonchi and Lakshmanan (2011) also study influence maximization, but use a data-based perspective. They create a 'credit distribution' model that estimates the expected influence spread in a social network, using propagation traces. The authors show that their approach selects very different and possibly better seed sets than approaches that use edge probability assignment (which is used in the other reviewed studies) to capture degrees of influence.

Trusov, Bodapati and Bucklin (2010) create a methodology for extracting strong links in a network that has mostly weak links, which is often the case in an online social network. Thereby, they develop an approach to identify users who most influence others' activity. This approach could be used to select the right seed nodes. The approach of Trusov et al. is based on the assumption that a correlation between a user's Facebook activity (i.e. number of log-ins) and his friends' Facebook activity reflects the influence of that user. Romero et al. (2011) add to the research on influence maximization by creating the Influence-Passivity (IP) algorithm. This algorithm is a predictor of the maximum number of clicks that a URL on Twitter can get.

Table 2 provides an overview of the reviewed literature that contributes to the research on influence maximization. Influence maximization provides one of the biggest opportunities in social media, since it allows users to influence a maximum number of people with a minimum effort. While the initial algorithm (Kempe et al., 2013) was not based on real data, the overview shows that recent studies are using various popular social networks to evaluate their approaches. The fundamental knowledge on information diffusion is available, but the right metrics have to be combined with the right approach (data-based or probability assignment) to achieve an optimal seed set. User attitude is identified as an important characteristic on which information diffusion depends, while no research is found on measuring this characteristic.

Table 2. An overview of the contributions to influence maximization.

Publication	Contribution
Kempe et al. (2003)	Develop an algorithm to select the optimal seed set.
Chen et al. (2010)	Design a scalable maximization algorithm (applicable to large-scale online networks).
Trusov et al. (2010)	Develop an approach to select users that significantly influence other users, based on log-in data.
Goyal et al. (2011)	Develop an approach that estimates expected influence spread, based on propagation in real data.
Romero et al. (2011)	Develop an algorithm that determines the influence and passivity of Twitter users and thereby predicts URL clicks.
Mochalova & Nanopoulos (2013)	Develop an approach that is based on information about the structure of a social network, instead of influence factors.

Beyond influence maximization, Chen et al. (2010) identify social influence mining as a topic for future research. This would improve knowledge on social influence processes and could aid marketers in improving their influence maximization approaches.

3.2 Applications

Social influence on social media is applied, measured and managed in a number of fields. Theories are often related to marketing theories and practices. Trusov et al. (2010) note that social influence has been the subject

of more than 70 marketing studies since the 1960s. The focus within application articles in this review is on marketing and business. Other identified fields are politics and leadership.

3.2.1 Mobilization

As Aral (2012) stated, social media automates social signals that could be used to promote widespread behavior. Politics is an interesting field for this mobilization. Bond et al. (2010) study whether political behavior can spread through an online social network by showing a statement on Facebook which encourages users to vote. With this study, the authors show that online political mobilization works. This is primarily caused by the fact that the influence spreads through strong-tie networks that exist offline but have an online representation.

Commercial mobilization is the dominant field of mobilization in social influence research. Publications are found on intention models and advertising. In their study on online shopping, Lee et al. (2011) show that positive informational influence improves the relationship between perceived ease of use and attitude towards online shopping. In addition, it improves the relationship between the attitude towards online shopping and the intention to shop online. More specifically, it is stated that messages affect online purchasing decisions through the social influence internalization process. The authors recommend online merchants to target marketing efforts at the beliefs and attitudes of potential shoppers.

3.2.2 Word-Of-Mouth

Word-Of-Mouth (WOM) is defined as the act of exchanging marketing information among consumers, and plays an essential role in changing consumer attitudes towards products and services (Katz & Lazarsfeld 1955). According to Bakshy et al. (2011), Word-Of-Mouth diffusion is an important mechanism by which information can reach large populations. It is therefore closely related to influence maximization. Bakshy et al. find that content seeded by marketers may diffuse differently than content selected by users themselves. maximization and prediction algorithms developed by marketers might therefore not operate as expected. Trusov et al. (2009) link WOM to new customer acquisition. Their study shows that WOM has an elasticity that is 20 times higher than that for marketing events and 30 times higher than that of media appearances. This emphasizes the impact of WOM on marketing practices.

Hennig-Thurau, Gwinner, Walsh & Gremler (2004, p. 39) define electronic Word-Of-Mouth (eWOM) as "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet". eWom is a relevant theme in social media due to the user-generated nature of the content on social media platforms. Chu and Kim (2011) find that tie strength, trust, normative influence and informational influence are positively associated with eWOM behavior on customers' favorite social networking site. This means that customers are more engaged in seeking, giving or passing their opinions on these sites if they have strong connections with their 'friends' and are susceptible to influence.

Chevalier and Mayzlin (2006) find that customer WOM affects consumer purchasing behavior at Amazon.com and bn.com and thereby show the effectiveness of social influence as an online marketing mechanism. Potential customers' purchase decisions are influenced by the opinions and experiences of others published online (Baum et al., 2013; Lee et al., 2011). Baum et al. research the impact of a social media campaign on the online WOM and referral behavior of customers and show that expectations of and satisfaction with a product can be influenced by the quality of the referral.

Bakshy et al. (2011) identify three benefits of WOM influence for marketers:
- Adopting more precise metrics of influence;
- Collecting more and better data about potential influencers over extended intervals of time;
- Exploiting ordinary influencers.

According to the reviewed studies, Word-Of-Mouth proves to be a highly effective concept in social media. Informational social influence (as identified by Lee et al., 2011) is one of the important mechanisms in WOM.

3.2.3 Online Reputation Management

In addition to Word-Of-Mouth, related research on Online Reputation Management and customer reviews is emerging in the field of marketing. Yang and Albers (2013) state that Online Reputation Management in the

context of Web 2.0 is far more challenging than Web 1.0 Online Reputation Management, due to the reach and the user-generated nature of the current internet. Trenz and Berger (2013) conduct a systematic literature review on online customer review studies in order to develop a research agenda for the topic. They find that studies on online customer reviews cover a limited set of products and websites. In addition, Trenz and Berger find inconsistencies in the reviews' effect on sales and identify the influence of helpfulness on customer decision making as an area for further research.

The strong effects of social influence in social media have implications for marketers. The influential impact of customer reviews and other user-generated content increases the importance of online reputation management. Romero et al. (2011) state that the knowledge of the least passive people in a network can be useful from the perspective of viral marketing. Marketers have to find the influential people, collect data on them and exploit their influence.

3.3 Online Social Influence Model

Based on the findings of our literature review, we developed a model that assists in managing social influence in the context of social media. This Online Social Influence Model uses the WOM benefits of Bakshy et al. (2011) in combination with the identified techniques for measuring and maximizing influence. Figure 2 presents the model, table 3 describes its steps.
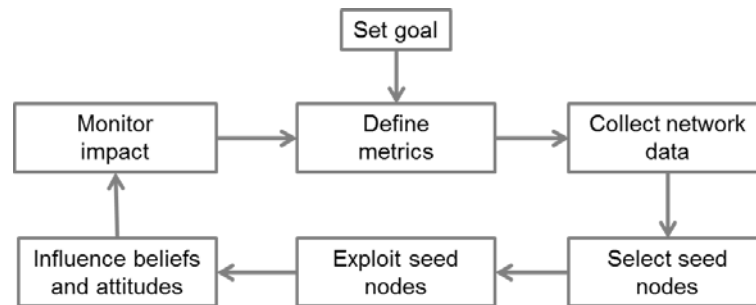

Figure 2. The Online Social Influence Model.

Table 3. The steps of the Online Social Influence Model.

Step	Explanation
Set goal	Define the goal of managing social influence. How should information diffuse and what should be the outcome?
Define metrics	Define the metrics that identify influential users. The current study shows that the focus should be on the attitude, centrality and tie strength of nodes.
Collect network data	Collect data on the network structure, using the metrics defined in the previous phase.
Select seed nodes	Using algorithms for influence maximization, a set of seed nodes can be selected that has the potential to reach a maximum number of network members.
Exploit seed nodes	Target the selected nodes to ensure propagation of the message. The exact implementation of this step depends on marketing strategies.
Influence beliefs and attitudes of all nodes	Make all network members comfortable with the propagated message and potential new messages.
Monitor impact	Evaluate whether the diffusion of information was influenced in the preferred manner. Based on the results, new metrics can be selected and new data can be collected.

This model assumes a high impact of influence maximization and thus strives to find the members that can be targeted to reach a large part of a network. In addition, it highlights the importance of making network members comfortable with messages, since various publications (Lee et al., 2011; Zeng et al., 2009) show

that this has a significant effect on the acceptance of a message (e.g. potential sales). The influence metrics are an essential element of this model. While we identified attitude, centrality and tie strength as the most important and relevant metrics, different cases might have a different mechanism of influence and thus different metrics. The reviewed literature focused on these structural metrics, but semantic metrics could also be considered. Further research is needed to study this type of metrics, before they can be included in the model.

4. CONCLUSION

By means of a structured literature review this research provides an overview of the state-of-the-art in the field of social influence through social media. There are multiple studies on the applicability of real world social influence theories in the online world, which show that the effects are comparable in the offline and online world. Other studies are mainly focused on measuring or exploiting social influence in an online context. Researchers are still trying to find the best social influence metrics and to solve the influence maximization problem. The diffusion of information depends on the centrality, attitude and ties of nodes in a network, which means that these characteristics should be measured. With this knowledge, electronic Word-Of-Mouth can be analyzed and potentially coordinated. All reviewed studies prove the high impact of social influence in the context of social media. It is essential for businesses to understand social influence mechanisms, select the right metrics, collect the right data and exploit the influence opportunities in social media. To model these elements, we created the Online Social Influence model, which provides high-level steps to manage social influence through social media.

This study contributes to research by describing the state-of-art research on the topic of social influence through social media, which could be used as a starting point for future research in this field. To practitioners, this study provides a starting point for the incorporation of social influence in their social media and marketing strategy. The Online Social Influence model should be helpful in devising these strategies. In addition, it serves as a starting point for defining more concrete step in effectively managing social influence through social media.

5. FUTURE RESEARCH

The reviewed field of study is very dynamic and provides many opportunities for future research. More research needs to be conducted to find social influence metrics that correlate with the actual influence of social media users. Most of the current research focuses on Twitter networks, more types of social media should be taken into account. In addition, there is still discussion on influence maximization and better algorithms can be developed. Since Goyal et al. (2011) find that a data-based approach provides better results than probability assignment, this is an important approach to study more elaborately.

Besides the study of Mochalova & Nanopoulos (2013), no research was found on finding metrics concerning the attitude of network nodes, while this is an essential characteristic. Measuring attitude should therefore be elaborated. Chen et al. (2010) identify social influence mining as an important topic for future research.. New knowledge could be implemented in the Social Influence Model, in order to create more concrete steps. The definition of metrics could be elaborated, but the influence on attitudes and the monitoring of results should also be researched.

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