Heliyon 5 (2019) e01677

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.heliyon.com

How to quantify social media influencers: An empirical application at the Teatro alla Scala

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ARTICLE INFO

Keywords:
Tourism
Business
Information science
Computer science

ABSTRACT

A topic of primary importance for organizations is the ability to identify and appraise Social Media Influencers (SMIs), given their key role in affecting conversations and interactions on social media. According to the current research in this area, influencers make up a single category of social media users, but only limited attention has been paid concerning the extent to which they can exert their influence. In this study, the quantification and classification of SMIs is addressed by proposing an advanced methodology based on social network analysis - K-shell decomposition - together with a discussion on the relationship between the different SMI categories and the effect of each type of influencer on the public relation activity of an organization. The developed methodology was tested through an action research project conducted at the Teatro alla Scala of Milan, and the results were then discussed with the management of the opera house. The main finding of this work is that SMIs can be split into writers, authorities or spreaders on the basis of the kind of influence they exert, thereby delivering a precisely focused typology of SMIs. These findings enhance our academic knowledge on analytics applied to social science, while also providing a real case situation where managers make practical use of analytics.

1. Introduction

Social Media Influencers (SMIs) play a key role in affecting the way users interact on social media, and organizations have learnt to leverage on this group when they prepare their communication and public relations plans (Freberg et al., 2011; Moreno et al., 2015; Li, 2016; Ge and Gretzel, 2018; Ong and Ito, 2019). SMIs represent “a new type of independent third party endorser who shape audience attitudes through blogs, tweets, and the use of other social media” (Freberg et al., 2011).

With their audience looking up at them as credible sources of information, SMIs can provide valuable support to organizations, while equally being a potential menace (Li, 2016; Ramadan, 2018; Ong and Ito, 2019). Influencers can promote a brand, enhancing an organization's popularity and becoming, in this way, part of the enterprise's social media strategy (Booth and Matic, 2011; Ge and Gretzel, 2018). A number of companies already promote their brand through blogs posted by famous bloggers or artists who mention a particular product or label on social media, often in connection with experiences in their daily life. On the flip side, influencers can also represent a hazard for organizations, when they point out bad results or negative situations involving the enterprise or, even worse, when they pass on false information, which can often originate from fake social media accounts, or when they actually write bogus material themselves (Freberg, 2012; Wan et al., 2015; Jahnke and Kroll, 2018).

It follows that organizations must engage proactively with social media influencers and plan specific communication strategies around them. In the available studies, an influencer is defined as someone who has been empowered by their network, is extremely active on social media and so makes a significant impact (Li, 2016). These studies, however, have not been concerned with classifying SMIs or examining how they connect with the personal relations strategies set in place within organizations. This implies that the overarching term of SMI brings together users who exert several kinds of influence. Influencers are, in some cases, those with very many followers, other times, they have a high number of connections or they may be extremely prolific bloggers (Himelboim et al., 2014; De Veirman et al., 2017; Djafarova and Rushworth, 2017). If influencers are taken as a single category of social media users, companies will find it difficult to set in place a public relations strategy customized to the kind of influence being exerted.

This study addresses the problem of how to evaluate SMIs, by focusing on the kind of influence that the SMIs hold. The following research questions are addressed in the paper:

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https://doi.org/10.1016/j.heliyon.2019.e01677
Received 29 October 2018; Received in revised form 1 April 2019; Accepted 3 May 2019

- What are the indicators for qualifying and quantifying Social Media Influencers (SMIs)?
- What is the methodological approach for applying these measures?
- How can SMIs be classified and what are the associated public relations strategies?

Theoretically, the development of indicators for the quantification of SMIs is grounded in Social Network Analysis (Wasserman and Faust, 1994), which recognises a different level of importance for nodes inside a network. Empirically, the indicators identified and related methodological approach were applied through an action research project conducted at the Teatro alla Scala, one of the major opera houses in Europe (and here also referred to as La Scala). Operationally, the authors conducted an empirical analysis of a Twitter-based dataset consisting of tweets posted about the Teatro Alla Scala in 2016, alongside interviews and meetings held with the opera house's marketing and communication offices.

As the main outcome of our study, we found that there are different types of SMIs, depending on the kind of influence they exert. This led us to come up with a precisely focused classification of SMIs into *writers, authorities and spreaders*. The activity and interaction of these influencers were captured and monitored through a set of indicators that have been tested at a technical and management level through the action research project.

The rest of the paper is structured as follows. First, the literature background consists of reviewing extant studies on influencers, with particular reference to the available measures for detecting SMIs. The research methodology will then be presented, followed by the results, where the first part covers the proposed indicators and the network-building methodology, and the second part deals with how these measures can be applied empirically to the Teatro alla Scala Twitter dataset. The final section contains the discussion and conclusions, expanding on the potential uses of these measures in management studies.

2. Background literature

There is the widespread recognition that social media users play different roles within social media platforms based upon their level of engagement with the production and consumption of information (Shao, 2009; Muntinga et al., 2011; Austin et al., 2012; Li, 2016; Ge and Gretzel, 2018). Independently of the various classifications of social media users, users are generally split into two main categories, active social media users and passive social media users (Li, 2016). While passive social media users are spectators watching from inside social media platforms, "active social media users are the creators, critics, collectors, and joiners" (Li, 2016: 51).

Influencers are considered to be a particular type of active social media user, and are defined as "opinion leaders who can use their online platforms to diffuse information and affect the attitudes and behaviours of their audiences" (Moreno et al., 2015).

The available management studies on SMIs address three main research streams (see Table 1).

The first research stream is focused on *the relationship between SMIs and other social media users*, with studies exploring how the general public perceive information posted on social media by SMIs, often comparing this information with that provided through traditional media (Hayes and Carr, 2015; Johnson and Kaye, 2015; Djafarova and Rushworth, 2017; Ge and Gretzel, 2018). The second research stream explores the *relationship between SMIs and the organization,* placing particular attention on how organizations manage their interactions with influencers (Jin and Liu, 2010; Pang et al., 2016 Ong and Ito, 2019). For example, Pang et al. (2016) developed a conceptual model to frame a strategy for cultivating effective relationships with SMIs, while Jin and Liu (2010) explored how organizations can interact with influencers to manage potential crises. A third recent research stream is concerned with the *personal characteristics of SMIs*. Concerning this last point, Freberg et al. (2011) adopted a California Q-sort method to provide a qualitative description of the salient personality traits of SMIs. The practices of self-branding and "micro-celebrity" used by social media influencers have been investigated in other studies, where the focus was on identifying and analyzing the behaviour of SMIs (Wiedmann et al., 2010; Khamis et al., 2017).

Despite this growing literature on SMIs, management scholars have, to date, given little attention to how influencers can be detected or appraised once identified. A proxy for quantifying influencers is sometimes obtained by counting the number of posts they publish, their followers, the hits they receive on social media channels or their connections (Himelboim et al., 2014; Agostino and Arnaboldi, 2017; Djafarova and Rushworth, 2017). The main disadvantage of these approaches is that the different kinds of influence exerted by SMIs, whether determined by the number of connections, posts from followers or something else, collapse into a single pigeonhole labelled influencer.

A small number of studies propose more sophisticated approaches to detect SMIs. For example, Booth and Matic (2011) developed a valuation algorithm, also called influencer index, that it is based on a weighted average of different parameters (such as posting frequency, citations, views per month and level of engagement). While this approach brings a number of different influencer-related characteristics into the elaboration, each of these characteristics on entering the index as variables must be classified manually - and so subjectively - on a scale from 1 to 5. The process of identifying influencers is, as a result, biased according to the analysts' individual perceptions. More recently, De Veirman et al. (2017) suggested that the ratio between the number of followers and of followees should be taken into consideration, since they found "that a high number of followers may negatively impact influencer likeability for influencers who are following few accounts themselves" (p. 813).

All these studies have increased our understanding of the role played by SMIs and their impact, but somewhat limited attention has been paid to the methodologies for measuring these SMIs. SMIs are seen as a single category of users, without looking at the different kinds of influence they can exert within their network. This study addresses this issue by proposing a methodology and a set of indicators theoretically grounded on social network analysis to quantify and classify SMIs.

3. Methodology

The study relies on action research. The distinctive feature of this approach is that the researchers and the organization under examination

Table 1
Current literature on Social Media Influencers (SMIs).

Research stream	Main insight	Authors
The relationship between SMIs and other social media users	Focus on the influence of SMIs on the general public (i.e. on the social media network)	• Hayes and Carr (2015) • Johnson and Kaye (2015); • Djafarova and Rushworth (2017); • Ge and Gretzel (2018).
The *relationship between SMIs and the organization*	Focus on the impact of SMIs on the organization	• Jin and Liu (2010); • Freberg et al. (2011); • Pang et al. (2016); • Ong and Ito (2019).
Personal characteristics of SMIs	Focus on the distinctive features of SMIs	• Wiedmann et al. (2010); • Frieberg et al. (2011); • Khamis et al. (2017).

Table 2
Phases of the action research project.

Action Research phase	Main activity	Main output
Diagnosing	• Defining the boundaries of the problem. • Clarifying the expected output from the project	• Research objective • Boundaries of analysis
Action Planning	• Defining the project agenda in detail	• Planning the project in terms of defining: • Social media • Time horizon for analysis • Keywords for data crawling • Techniques for data cleaning • Method for constructing the network
Action Taking	• Data crawling from social media • Data cleaning • Data analysis	• Preliminary set of indicators to detect the influencers
Evaluating	• Intermediate discussion on the results obtained	• Refining the proposed indicators for the analysis
Specifying Learning	• Consolidating the analysis	• Preparing final report and analysis for internal distribution

work together within a joint research framework, allowing them to address a matter that can be both a practical concern and an academic problem. In this study, the organization in question is the world-famous Teatro alla Scala. La Scala was established in 1778 as an independent opera house, eventually becoming a foundation in 1997. It started operating on social media in 2009 and is now active on five social media platforms, Facebook, Twitter, YouTube, Instagram and Pinterest.

A work group was set up at the beginning of the project consisting of four researchers and five opera house employees, with the theatre being represented by the head of marketing and that of communications, the social media manager and two social media and communication specialists. The research group was made up of two senior researchers with expertise in management and analytics, one researcher with specific expertise in social media management and one with statistical expertise. The project lasted twelve months in total, with a monthly strategic meeting between the senior researchers and the heads of marketing and communication, and a weekly operational meeting between the junior researchers and the social media manager and experts. One researcher spent three days at La Scala as a participant observer, taking note of the daily dynamics of their social media management and analysis.

The entire project can be discussed following the five main phases of action research (Table 2), expressed as diagnosing, action planning, action taking, evaluating and specifying learning (Susman and Evered, 1978).

The *diagnosis phase* consisted of setting out clearly the problem of analyzing SMIs. In this phase, the literature review played a key role in clarifying our understanding of current public relations research on SMIs. In particular, a gap emerged between quantifying the SMIs and their different levels of influence. This academic problem was aligned to the practical objective of being able to gain a better understanding of the social media users who talk about the opera house, an aspect that would allow La Scala to adjust their marketing and communications strategies accordingly. The theatre's management explained that they were interested in detecting the most influential bloggers engaged in talking about La Scala, their function or role (whether they are competitors, journalists or other) and their power within their social media network.

The *action planning phase* consisted of setting out the approach for the analysis, in terms of identifying the social media to be analyzed, defining the time horizon for collecting data and the keywords for extracting data, the techniques for data cleaning and the approach for building the network of social media users. At the end of this phase, the decision was to concentrate on the social media Twitter, since data can be downloaded for free (https://developer.twitter.com/), which is not the case for Facebook or Instagram. A further decision was made to gather data from social media conversations by keywords rather than by account, allowing the group to detect conversations about the opera house more broadly, rather than only the threads emanating from tweets posted by La Scala.

The *action taking phase* consisted of putting previous decisions into practice. Data were downloaded from Twitter from March to May 2016 using its public API (Application Programming Interface), the network of social media users was constructed and the indicators for detecting influencers elaborated following a data-driven approach.

The *evaluation phase* played a crucial role in terms of revising the completed analysis, a process that involved both the research team and the opera house management represented by the heads of communication and of marketing. The indicators for detecting the influencers were refined during this phase, and the empirical analysis amended accordingly.

Finally, the *specific learning phase* took place after the analysis was fine-tuned. This involved holding a final meeting to consolidate the empirical analysis as well as the general methodology for detecting influencers.

The results presented were derived from a data-driven analysis of the Twitter dataset, backed by extant theories on SMIs and discussions with the management of the opera house.

4. Results

Two main areas of results can be identified. A first area concerns the theoretical development of indicators to detect SMIs, together with the methodology used to construct the network. The second area of results applied the indicators previously discussed to the Twitter dataset concerning La Scala.

4.1. Detecting differences between SMIs: hub index, authority index, and centrality index

Our argument states that SMI is a generic term that refers to an active and empowered social media user who is listened to and seen as a trusted source by other social media users. They central point of our study is that there are different classes of SMIs, depending on the specific kind of influence that the SMI is able to exert. This premise is fundamental for establishing that there is not one but several types of SMIs, and that these different kinds vary one from another. As previous literature suggests (Booth and Matic, 2011; De Veirman et al., 2017; Djafarova and Rushworth, 2017), a SMI can be actively engaged in posting on social media, or can have scores of followers or connections. In turn, these different levels of activity call for a change in how SMIs are measured. Different metrics are required to detect the heterogeneity in SMIs. In order to develop ad hoc measures for quantifying SMIs, we endorsed advanced social network analysis techniques basing the classification of SMIs upon the role they play in the network.

Since social network analysis focuses on patterns of relationships between nodes, this method is particularly useful for investigating the structure of a network in terms of the relative importance of the nodes and the strength of their ties (Wasserman and Faust, 1994). Social network analysis techniques are increasingly being adopted to investigate social media networks, especially the connections and interactions between social media users or heterogeneous roles inside a network (Sedereviciute and Valentini, 2011; Himelboim et al., 2014; Ramos et al., 2019). In studies endorsing the social network analysis perspective, this approach is recognized to be "a natural form of understanding and evaluating public relations as it focuses on patterns of relationships among social entities" (Himelboim et al., 2014: 363–364). Other authors have argued that "in a social media context, the network perspective becomes vital to tackle since social media are also about networks and stakeholders who create and share information online" (Sedereviciute and Valentini, 2011: 227).

In accordance with social network analysis, the position of a node in the network can affect its power and influence (Granovetter, 1973; Wasserman and Faust, 1994; Coombs, 1998). The relative importance of a network node is usually measured through a set of indicators that can include centrality, degree and hubs, which determine the number of connections, the strength of the connections and the relative position of a node with respect to other nodes (Freeman, 1979; Wasserman and Faust, 1994).

In this study, we propose a novel application of the social network analysis to quantify social media influencers and identify the different kinds of influence they can exert (Alp and Öğüdücü, 2019; Oro et al., 2018). Moreover, without the adoption of powerful and advanced analytical tools of network analysis, a deep understanding of users roles and behaves would be more difficult. To do this, it is necessary to build a network of social media users, where the nodes and connections start from social media conversations.

More specifically, the network considered is what is known as a "citation network". Given a set of posts relating to the Teatro alla Scala (based upon certain keywords and written within a certain interval of time), each post or user mentioned is a node in the network and every link between two nodes represents a citation. For example, looking at the following post:

> "'Due Foscari' with great @user2 at @teatroallascala –amazing weekend in Milan #travel #milano"

written by an author going under the name of "@user1", this gives rise to three nodes (corresponding to "@user1" and the two users named in the post, "@user2" and "@teatroallascala", and to two directed links, the one from "@user1" to "@user2" and the other from "@user1" to "@teatroallascala". Using the same approach for all the posts downloaded, the result is a weighted and directed network where the nodes represent the users posting online or being cited in posts, and the interactions are given by the messages exchanged between users.

After building the network of social media users, the indicators used to quantify SMIs can then be derived. We adopted already developed indicators in social network analysis dealing with the importance of nodes within a network (Granovetter, 1973; Freeman, 1979; Wasserman and Faust, 1994), but applying them in a novel context of SMIs and completing this with more advanced statistical methods for investigating how information propagates through networks. This resulted into the development of three main indicators, hub index, authority index and centrality index (Table 3). These three indicators show three different perspective of the user's activity, that could be interpret as three different category of SMI.

The hub and authority indexes come from the web search engine sector and were initially introduced to find the best way to organize relevant information. The *hub index* describes how active a user is in writing to important users in the network, and ranges from 0 to 1 (these being the lowest and highest level of hubness, respectively). Users with a high hub index are here called "*writers*" as they send the most messages to important users in the network. The *authority index* describes how widely cited a user is by users with a high hub index, that is, by top writers, and it also goes from 0 to 1 (the lowest and highest level of authority, respectively). Values close to 1 detect what we called here "*authority*". Operationally, given a graph G=(N,V) with N nodes and V links, if A is its adjacency matrix, the hub index is computed as the eigenvector of the matrix AA^T, while the authority index is computed as the eigenvector of the matrix A^TA.

Hub and authority indexes are strongly related to the concept of activeness and passiveness of a user within a network. User activeness (out-degree) and passiveness (in-degree) are computed by counting the number of messages sent and received (Wasserman and Faust, 1994). However, hub and authority extend the concept of degree, because they take in the mutual relationships between highly passive and highly active users. The two indexes, hub and authority, present what is known as a "mutually reinforcing relationship", meaning that a user with a high hub index, otherwise known as a "good hub", is a user who points to many "good authorities", where a "good authority" is a webpage with pointers from many "good hubs".

The *centrality index* help to identify the SMIs who are mentioned often, have numerous connections and, most importantly, occupy a central position in the network, as they are closest to the focal organizations. The idea of centrality in social network studies is that a node with high centrality has higher access to information and has greater power than others (Granovetter, 1973). SMIs with these features here have been called *spreaders* given their high potential for propagating information throughout the network. Extant literature on social network proposes a variety of indicators to quantify the level of centrality for a single node, such as betweenness centrality or closeness centrality (Freeman, 1977; Granovetter, 1973). For the purpose of detecting SMIs, here we have adopted a more advanced social network technique, called the *K-core* or *K-shell* decomposition algorithm, using it to detect the level of centrality and, therefore, identify the spreaders. This approach is widely adopted when investigating the spreading of certain phenomena, such as infections, epidemics and other diseases (e.g. Pastor-Satorras and Vespignani, 2001), and is therefore aligned to detecting who, inside the social media network, has most spreading power.

The basic idea behind applying K-shell decomposition to the task of identifying SMIs is that network users positioned in central core layers can spread messages more widely than users located in peripheral areas. Hence, the users positioned closed to the centre (where the focal organization is located) are those influencing the network and they can easily spread messages throughout the network.

Operationally, the K-shell decomposition algorithm works in the way described below (Kitsak et al., 2010):

> "nodes are assigned a k shell according to their remaining degree, which is obtained by successive pruning on nodes with degree smaller than the k-s value of the current layer. We start by removing all nodes with degree $k = 1$. After removing all the nodes with $k = 1$, some nodes may be left with one link, so we continue pruning the system iteratively until there is no node left with $K = 1$ in the network".

This approach is performed iteratively until no more nodes are left. In our empirical application, we concentrated on the in-degree of each node. The idea is to prune the network by peeling away the outer layers as if it were an "onion", until reaching the core. Three layers were

Table 3
Categorization of SMIs and relative indicators.

Indicator	Description	Category of SMI
Hub Index	Social media users are sorted on the basis of the total number of messages sent to important users.	Writer
Authority Index	Social media users are sorted on the basis of the number of messages received from the most active users.	Authority
Centrality Index	Social media users are sorted on the basis of a k-shell decomposition analysis (considering the number of citations and connections)	Spreader

identified in our application, with users in layer K = 3 representing the central nodes of the network (those nearest to the organization) and they are considered as the spreaders. These are users cited the most on the organization's social media profile, and are, therefore, users that the network as a whole associates most closely with the organization. Because of the number of citations they receive and their many connection, spreaders are strategically important for an organization.

4.2. Detection of SMIs in the twitter network of the Teatro alla Scala

This section discusses the empirical application of the proposed indicators for detecting SMIs on the Twitter dataset relating to the Teatro alla Scala.

In line with the methodology proposed, the social network was constructed from the downloaded dataset (see Fig. 1). The Twitter network held 3,080 social media users and 13,318 posts written over the period of the analysis (March-May 2016). The Teatro alla Scala, being the focal organization, is positioned at the centre, while each user is indicated as a green node, the size of which is proportional to its degree.

The three indicators were then applied to detect the three different categories of influencers.

On elaborating the hub index, the influencers were ranked on the basis of their sent messages. We took the top ten users and analyzed them further. From the accounts and features of these users, we found that there are many kinds of writers in the theatre's Twitter network. Most are members of the general public, but some are artists, employees or companies. All are influencers, citing La Scala very often in their social media conversations. At this point, it is clearly important to understand whether they talk about La Scala in a positive or negative manner and what their level of authority is.

Users with a higher authority index were identified as a group of influencers whom we have called authorities. The first authority in the network was inevitably the opera house itself, given that the network was built around the focal organization placed at its centre. Behind the theatre, the next authorities were artists at La Scala and companies. The artists were mainly dancers, given their popularity among the general public, while companies are often the opera house's main sponsors.

Finally, the k-shell method was used to detect the spreaders. Only 15 users were found in the inner layers, corresponding to the key network spreaders for La Scala. Once again, artists and companies appeared to be the mainstay of the category (Table 4).

The results of this analysis were discussed with the management of the opera house. This phase was important in terms of interpreting the results of the three indexes, both from their viewpoint and from a management perspective in general. The values for quantifying the SMIs presented in Table 4, alongside with the discussion of these results with the theatre's management, supported a broader discussion on how these measures affect the public relations actions of an organization. More specifically, per each type of influencer, an ad hoc public relations action was identified (see Table 5).

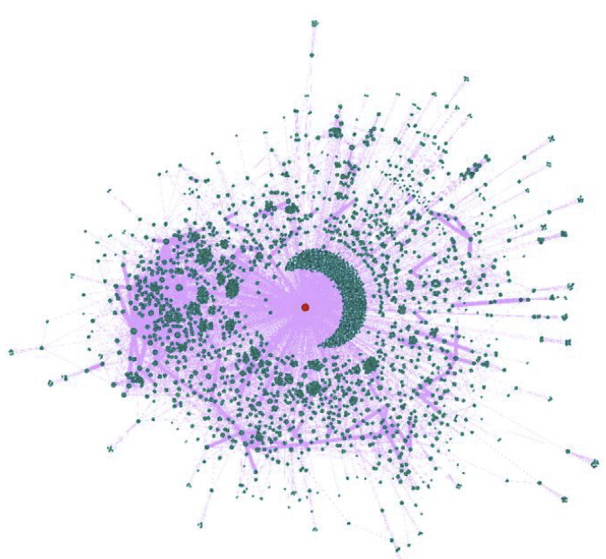

Figure 1. Social Network of Twitter users for Teatro alla Scala.

Spreaders are a typology of SMIs particularly adept at conveying messages to the broader network, and as such they can act as strategic actors for organizations, helping to spread information and/or promotions. An organization should be proactive and contact these individuals, engaging them (and their services) within its communication plans and for other public relations activities. The discussion with the management of Teatro Alla Scala supported this view, with a reflection on the possibility to establish communication agreement with social media account detected as "spreaders". Accordingly, the detection of spreaders within the network of social media users pushes the organization to adopt an "active" public relation strategy characterized by the active involvement of the spreaders themselves in conveying social media messages.

Authorities represent a typology of SMIs that receive a vast number of messages and, for this reason, are considered to be important in the eyes of other users in the network. Often, they are also social media accounts with a high number of followers. Their role is crucial inside the network of social media users, having the power to boost positively or negatively the opinion of other users. If "authorities" post messages expressing a positive sentiment, then this can strengthen the brand's reputation they refer to. If, on the contrary, they post negative messages, this can cause damage to a brand. The detection of "authorities" within the network has the main effect to push organizations adopting a "monitoring" public relation action on these social media account. A monitoring action means the introduction of "alert" to signal the publication of a post by "authorities"; the subsequent action depends on the sentiment of the message itself: positive messages can be forwarded (recalling the active action), while negative messages require an immediate intervention to avoid the diffusion of a negative mood among the other social media users. Moreover, the strategy towards authorities can also be proactive, by involving them in the communication activity by the organization and leveraging on their wide network to boost the virality of the messages.

Finally, "writers" are the third categories of social media influencers, quantified by the hub index as those social media users very active in writing messages. The discussion of the list of "writers" with the management of Teatro Alla Scala, lead to the identification of several private individuals and a few organizations and companies. The connected public relations activity was dual: for writers with a high amount of followers, they were included in the monitoring activity previously described. Yet writers with a limited amount of followers were mainly considered as spammer. The action implemented was that of ignoring them. This implies the adoption of an inactive action only for those writers with a limited amount of followers.

In summary, advanced social network analysis techniques were specifically applied to the novel context of detecting heterogeneous SMIs. Indicators were proposed theoretically, but also applied empirically with the identification of three main public relation actions (in connection with each typology of SMI identified) derived from the discussion of results with the management of Teatro Alla Scala. We are aware that other effects can exist, such as the level of engagement connected with the messages post by influencers or the sentiment of the messages. However, the analysis of the effects of SMIs action is out of scope of this investigation.

5. Discussion and conclusions

Given the widespread recognition about the importance of SMIs in management studies (Freberg et al., 2011; Moreno et al., 2015; Li, 2016),

Table 4
Detection of SMIs of Teatro alla Scala.

Hub index		Authority index		Centrality index K-shell = 3
Twitter name	Value	Twitter name	Value	Twitter name
private individual	1.0000	company	1.0000	journalist
employee	0.8828	artist (dancer)	0.1080	artist (soloist)
private individual	0.6902	artist (dancer)	0.0768	company
private individual	0.5836	company	0.0486	company
private individual	0.4029	company	0.0435	artist (dancer)
private individual	0.3969	artist (dancer)	0.0208	artist (dancer)
private individual	0.3553	artist (choreographer)	0.0197	artist (dancer)
company	0.3443	artist (dancer)	0.0174	artist (choreographer)
artist (dancer)	0.3072	artist (soloist)	0.0168	artist (dancer)
company	0.2828	artist (dancer)	0.0105	artist (dancer)
private individual	0.2627	artist (dancer)	0.0102	artist (dancer)
association	0.2302	artist (dancer)	0.0100	artist (dancer)
company	0.2249	company	0.0094	artist (dancer)
private individual	0.2220	artist (dancer)	0.0093	artist (dancer)
private individual	0.2123	artist (conductor)	0.0090	artist (dancer)

this study addressed the question of quantifying SMIs, examining how they can be identified and how to classify them on the basis of the influence they exert.

Our argument here is that SMIs are not a homogenous category of users, and their influence on social media varies. This implies that there are different categories of SMIs. Previous studies were valuable in suggesting ways to detect SMIs and investigate their personal features and the impact of their activities on other social media users and the organization (Booth and Matic, 2011; Himelboim et al., 2014; De Veirman et al., 2017; Djafarova and Rushworth, 2017). Adding to previous research, this study also addresses how SMIs can be classified by proposing an advanced methodology based on social network analysis, and then examines the relationship between the different SMI categories and the personal relations strategies set out in an organization.

These results have been achieved through an action research project, which started from a literature review, proceeded with the empirical analysis on a Twitter dataset and concluded with a critical discussion of the results achieved with the management at La Scala. Moreover, once these measures were applied, they supported our initial argument that SMIs are heterogeneous, since the writers, authorities and spreaders all differ from one another.

The theoretical developments and empirical application enhanced previous research at two levels. First, we developed and tested the classification of SMIs, meaning that the associated methodology can be replicated in other studies. SMIs are grouped into three categories, revealed by the quantitative analysis of the network. The first category is that of the *writers*, detected through a hub index, and they are influencers in terms of the number of posts they write.

The second category is that of the *authorities*, that is, the influencers who are mentioned extensively within the network, and they were detected through an authority index. The third category is that of the *spreaders***,** who were detected by adopting a K-shell decomposition algorithm. These are the influencers who are mentioned very often and have many connections and, therefore, are very likely to convey information throughout the network.

Table 5
Public relation activity for the each category of SMI.

Type of influencer	Public relation action	Action description
Spreaders	Active action	Engage them to convey messages
Authorities	Monitoring action	Insert an alert for authorities posts and intervene when they post messages with a negative spin or leverage on them to boost the virality of social media messages
Writers	Inactive action	Do not consider overly busy writers with few followers (“spammers”)

This classification and methodology add to our current understanding about the importance of SMIs and how they can be detected, by underlying the importance of classifying influencers on the basis of the kind of influence they exert within the network.

The second area of results was obtained by applying the methodology empirically to La Scala, taking in insights from the participant observation process, and then validating the results. We are well-aware that our findings are specific to their context and time, however, this action research study allows us to draw more general considerations on public relations strategies in connection with the detailed analysis of SMIs. In particular, the empirical analysis confirmed that there are differences between the three categories of influencers, setting out a personal relations strategy for each group. The strategies can be split into “active” strategies, applied to spreaders, because of their central role in conveying messages through their network, “monitoring” strategies, applied to authorities, because of their numerous connections and their ability to deeply affect, positively or negatively, the reputation of organizations, and “inactive” strategies, applied to writers with only a few followers.

These results not only enhance our academic knowledge about SMIs, how they can be detected and the need for an ad hoc strategy for each type. The proposed methodology can also help public relations practitioners by providing them with a practical toolkit to detect SMIs and suggesting appropriate management strategies for each category.

This work can lead to further studies, where the same measures can be applied to other social media and used to explore the connection between SMIs and the opinions expressed in their posts.

Declarations

Author contribution statement

Agostino Deborah, Arnaboldi Michela, Calissano Anna: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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