SOCIAL MEDIA MANAGEMENT STRATEGIES FOR ORGANIZATIONAL IMPRESSION MANAGEMENT AND THEIR EFFECT ON PUBLIC PERCEPTION

Abstract

With the growing importance of social media, companies increasingly rely on social media management tools to analyze social media activities and to professionalize their social media engagement. In this study, we evaluate how social media management tools, as part of an overarching social media strategy, help companies to positively influence the public perception among social media users. A mixed methods approach is applied, where we quantitatively analyze 15 million user-generated Twitter messages containing information about 45 large global companies highly active on Twitter, as well as almost 160 thousand corresponding messages sent from these companies via their corporate Twitter accounts. Additionally, we conducted interviews with six social media experts to gain complementary insights. By these means, we are able to identify significant differences between different social media management strategies and measure the corresponding effects on the public perception.

Keywords: Strategic Social Media Management, Mixed methods approach, Impression Management, Receiver Operating Characteristic Analysis, Twitter, Public Perception.

1. Introduction

Over the last decade, social media platforms (SMPs) attracted a lot of attention and are established as an additional channel for communicating and broadcasting information (Aral et al., 2013; Shi et al., 2014). This development has changed the role of Internet users from mere information consumers to active information contributors (Larson and Watson, 2011). In this sense, individuals not only disclose how they are related to each other or what opinions and interests they have, but also set off market trends by influencing the public about topics, products, or companies. The fast and effective dissemination of user-generated content in SMPs results in an extensive sharing of information about companies and their products as digitized word of mouth among its users (Dellarocas, 2003; Kaplan and Haenlein, 2010). Shared information has a significant influence on (potential) consumers' as they rely more and more on the opinionof others (Rindova et al., 2005). Hence, the digitized stream of information from social media is important for companies to consider. Such impact is even intensified when shared information contains less favorable or negative statements about a company, product, or service (Baumeister et al., 2001; Kimmel, 2010). Thus, to benefit from social media, companies need to build up capabilities to monitor activities on SMPs and to engage with the community in a positive manner. By applying social media analytics, companies can monitor the user opinions about them, their products and services to obtain important feedback for improvements (Kaplan and Haenlein, 2011; Larson and Watson, 2011). In turn it may help lowering costs for research and development by learning directly from the customers about their needs (Parent et al., 2011; Dong and Wu, 2015). Accordingly, Apple bought a social-media analytics company to enhance their analytics capabilities and to gain access to the full stream of Twitter data (Wakabayashi and Macmillan, 2013). Moreover, based on the large interest in financial topics on Twitter (Greenfield, 2014) and the growing research on the connectedness of social media and stock markets (Chen et al., 2014) stock exchanges like the NASDAQ and NYSE use social media monitoring to provide investors with stock-related social media information for decision support (NASDAQ, 2012; Intercontinental Exchange, 2013). Monitoring social media is also important to determine the success of engagement activities and needs to be measured and compared with other business performance indicators (Hanna et al., 2011). Hence, companies are increasingly interested in social media to collect valuable information about potential customers (Culnan et al., 2010).

Besides monitoring social media activities to understand what is happening on social media, companies can take advantage of social media for their own business purposes (Culnan et al., 2010; Miller and Tucker, 2013). In general, the active management of corporate social media accounts has been found to positively influence the volume of user-generated content and thus stimulating the public debate about the company (Miller and Tucker, 2013). From a technological perspective, companies have the possibility to engage on SMPs by either using the SMPs' Web-frontend or to deploy more sophisticated SMM tools (e.g., Hootsuite, Salesforce, Spreadfast). These tools provide monitoring capabilities (e.g., sentiment, influencer, or trend analyses) and help to professionalize the workflow for user engagement (e.g., multi-user management, scheduled sharing, or automated replies). Independent ofwhether a company deploys specialized SMM tools, its SMM strategy needs to be aligned with the strategic goals of the company to be effective (Culnan et al., 2010). For example, if the revenue of a company is directly related to the image and the public perception of it, then actively influencing this perception is critical for business success. However, it remains challenging to make a strategic decision about the appropriate level of engagement in order to not only increase the share of message but also improve the public perception about the company. Hence, companies need to come up with a strategy about their engagement in social media to have a positive impact on the companies' public perception (Culnan et al., 2010). Among others, companies have to select the SMPs they want to be active on, decide on the purpose of their engagement (e.g., customer care, marketing, etc.), determine the extent to which they want to enter into dialogue with the users and much more. As companies are forced to be active on different SMPs, SMM tools provide functionalities to deploy a holistic management across the different SMPs (Kaplan and Haenlein, 2010).

So far, there is only little research investigating how companies should manage their social media activities and whether SMM tools are suitable to support their goals (e.g., Miller and Tucker, 2013). Thus, Aral et al. (2013) and others call for more research about the strategic use of social media at the organizational level. In this paper, we address this call and analyze the impact of different SMM strategies on the resulting public perception in social media. Accordingly, our aim is to enhance the understanding of how a professionalized social media engagement influences the perception of company in social media. Thus, we are interested in *how companies can influence their perception among social media users and which social media strategy should be applied to achieve it?* To address this question, we analyze approximately 15.5 million user-generated Twitter messages (tweets) containing information about the 45 most active Twitter-using companies from the Fortune 500 list, which we collected between October 2012 and June 2013. For the same period, we also extracted 159,815 messages sent from the primary corporate Twitter accounts of these companies. The analysis of the content and the metadata of the user- and company-generated tweets allows us to not only identify significant differences between the SMM strategies applied but also to measure the corresponding effects on the public perception. To allow a rich interpretation of the results from our quantitative study we conducted semi-structured expert informant interviews in a sequential mixed methods research approach.

The remainder of this paper is structured as follows: In the next section, we start elaborating on extant literature dealing with the theoretical foundations of organizational impression management. Subsequently, our hypotheses are stated before we introduce our mixed methods research approach in section four. Afterwards, in section five, we discuss our findings from the quantitative and qualitative study and integrate the results in the context of the existing body of knowledge. The paper concludes with the theoretical and practical implications, restrictions, and recommendations for further research.

2. Organizational Impression Management to Influence the Public Perception

Companies engage in social media in order to get in contact with the public in a positive way. Generally, the way in which individuals and organizations perform activities to influence the public are described by theories of self-presentation introduced by Goffman (1959) and impression management developed by Schlenker (1980). The concept of self-presentation describes how individuals play conscious or unconscious roles in everyday life to positively influence other people's impression of oneself (Goffman, 1959). Hence, self-presentation is a self-centered concept dealing with what an individual does in its own interest. Impression management, the broader concept, describes how individuals engage in activities to control or influence the perception of the public about themselves, other individuals, groups, or organizations (Schlenker, 1980). Therefore, impression management differs from self-presentation concerning the benefiting party of the actions. Most often the impressions made aim at establishing a positive and favorable image of an individual or a group in question (Wayne and Liden, 1995; Rosenberg and Egbert, 2011). The motivation behind this is the desire to achieve a specific public perception or to correct differences of what is perceived by the public with what is desired to be perceived (Leary and Kowalski, 1990). The extent to which impressions are made depends on the motivation to manage impressions and on the importance of the resulting public perception.

Based on the assumption that individuals can apply impression management to control the public perception about others like groups or organizations, impression management is also applied on the organizational level (e.g., Carter, 2006; Bolino et al., 2008; Highhouse et al., 2009). Thus, companies make use of impression management activities for presenting themselves in a positive way (e.g., supporting charity organization) to maintain a positive public perception (Elsbach and Sutton, 1992; Carter, 2006). Thereby, companies pursue impression management for a variety of reasons: e.g., to deal with product complaints (Conlon and Murray, 1996), to face social movement boycotts (McDonnell and King, 2013), to enhance financial outcomes (Schniederjans et al., 2013), or to present organizational performance (Staw et al., 1983). Engaging with the public to present information is important to create and maintain the desired public perception of a company's activities amongst the general public (Carter, 2006). Companies have several channels for engagement available, like issuing written statements such as press releases (Westphal and Zajac, 1998) or using mass media such as television or websites (Winter et al., 2003). With the rise of social media, companies have also the opportunity to deploy organizational impression management by engaging in social media as a complementing channel to influence and control how a company is perceived by the public (Aral et al., 2013; Schniederjans et al., 2013). Companies share information on SMPs to build their brand image, advertise their products, provide customer service, involve users in the product development process, and show corporate social responsibility (Culnan et al., 2010).

3. Research Model: Social Media Management Strategies

In line with our preceding discussion, we argue that the public perception of a company is related to the organizational impression management a company deploys (Highhouse et al., 2009). Literature points out various impression management tactics for companies to improve their public perception (Mohamed et al., 1999): Companies can use an assertive tactic to enhance or sustain a positive impression or a defensive tactic to defend from negative events. These tactics in turn comprise a variety of actions that can be applied to achieve a certain perception in the public, e.g., exemplification, boasting, prosocial behavior, or boosting (Bolino et al., 2008). Selecting the appropriate tactics to engage in social media conversations or to react on activities in social media is crucial for companies (Schniederjans et al., 2013). In this regard, deployment of SMM tools enhances companies monitoring capabilities of social media activities to select the appropriate organizational impression management tactics. Hence, we argue that the public perception of a company in social media depends on the SMM strategy that a company deploys.

In our paper, we follow the approach of Oh and Pinsonneault (2007) and argue that differences in the deployment of information systems are related to differences in IS strategies. Hence, we differentiate SMM strategies based on the use of SMM tools. In the case of Twitter, companies can either use the Twitter web-frontend to contribute messages through their corporate account or they can use more sophisticated, professional SMM tools to support organizational impression management to influence the company's public perception. Influencing the perception of the public about a company can be achieved by identifying most influential members of a SMP and positively influence them to gain them subsequently as a public advocate for the company (Cha et al., 2010). Leveraging the social structure of a SMP may even allow companies to lower advertisement costs by getting certain brand images broadcasted among their followers (Zubcsek and Sarvary, 2011). SMM tools also help to process messages by applying social network analysis, data mining or natural language processing to determine the public perception or sentiment regarding certain topics (Hu and Liu, 2012). Thus, companies can for example efficiently deploy defensive impression management tactics by swiftly responding to negative user comments (Mohamed et al., 1999).

Reflecting existing literature, our underlying research model to analyze the impact of different SMM strategies on the public perception in the case of Twitter is illustrated in Figure 1. We conceptualize public perception based on two concepts from marketing research – word of mouth and attitudinal loyalty. Word of mouth communication describes the sharing of information through communication from person to person (Godes and Mayzlin, 2004; Dellarocas, 2006). The concept of word of mouth consists of the key attributes valence (e.g., positive or negative tonality of opinions) and volume (e.g., amount of shared information) of the shared information (Chen et al., 2011). The reach of word of mouth is intensified by the core functionality of social networks to connect a large number of users with each other (Libai et al., 2013), but also the valence dimension plays a crucial role on SMPs considering e.g. the rapid diffusion of negative remarks (Dellarocas, 2003). However, research has shown that SMPs also allow management of user-generated content (Trusov et al., 2009; Kozinets et al., 2010). Thus, a company can enhance the word of mouth by successfully applying impression management in social media (Schniederjans et al., 2013). The second concept – attitudinal loyalty – defines a users' commitment toward a company (Chaudhuri and Holbrook, 2001). On SMPs, users are able to show their commitment to a company by connecting themselves with the company (e.g., by following or favoring), independent from their ability to purchase an organization's products (e.g., luxury goods). Nonetheless, the social media-based connection with a company is a strong predictor of becoming a company's customer (Clark and Melancon, 2013). The subsequent impact of more loyal users in social media is that shared information about a company diffuses faster in the SMP. This is because of the availability of more connections for relaying content to use the word of mouth effect as loyal users are more committed to spread information. Therefore, the strategic use of SMM to pointedly deploy organizational impression management in social media can help to increase the word of mouth and loyalty of users regarding a company (Clark and Melancon, 2013; Schniederjans et al., 2013). Thus, we hypothesize:

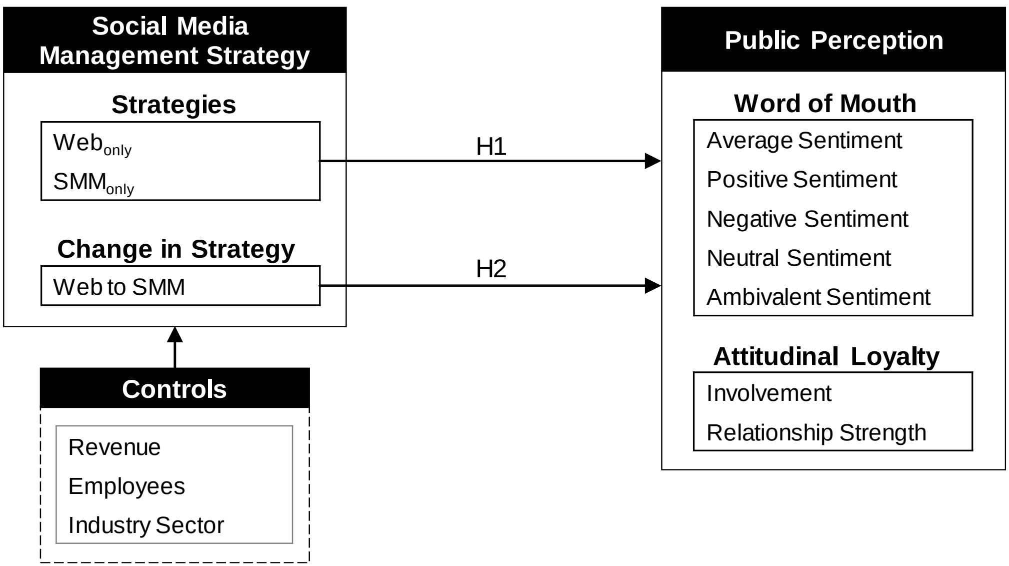

Fig. 1. Research model for analyzing the impact of different social media management strategies

Hypothesis 1: The implementation of a social media management tool improves the public perception of a company in terms of better word of mouth and a higher attitudinal loyalty of the users.

Hypothesis 2: The change of social media management strategies to the implementation of a SMM tool improves the public perception of a company in terms of better word of mouth and a higher attitudinal loyalty of the users.

4. Analyzing the Impact of Social Media Management

In order to address our research question of *how companies can influence their perception among social media users* we conducted an empirical study. Specifically, we analyzed *which social media strategy should be applied*, in terms of whether or not the application of a professional SMM tool helps to improves the companies' word of mouth and attitudinal loyalty with the users. Figure 2 depicts our mixed methods research approach. A mixed methods approach combines quantitative and qualitative methods to enhance insights on a phenomenon (Venkatesh et al., 2013). This approach is especially of interest in social media research where large datasets are analyzed highly automatically and quantitative and qualitative methods can increase knowledge (Ågerfalk, 2013). The quantitative study was guided by Fayyad et al.'s (1996) knowledge discovery process for big data analytics which has been applied so far in several studies in information systems research (e.g., Shaw et al., 2001). Previously, the approach had been applied predominately in computer science for structuring the steps of data mining. We decided to pursue a sequential mixed methods approach to qualitatively explore the underlying mechanisms of our quantitative results further. Considering that this study applies the established impression management theory to the novel context of social media management, we decided to conduct the complementary qualitative interviews following the quantitative analysis to increase the robustness of our findings (Venkatesh et al., 2013). Thereby, we were able to draw richer interpretations from our results through meta-inferences from both studies.

Quantitative Study					Qualitative Study
1. Data collection	**2. Data Selection**	**3. Cleaning and Preprocessing**	**4. Transformation**	**5. Data Analysis and Results**	**6. Complementary Interviews**
▪ Company- and User- generated Tweets ▪ Twitter Metadata ▪ Secondary Data	▪ 50 Companies ▪ 17m User-generated Tweets ▪ 200.000 Company-generated Tweets	▪ Message Preparation ▪ Language Detection ▪ Sentiment Analysis	▪ Dependent Variables ▪ Independent Variables ▪ Control Variables	▪ Strategy Comparison ▪ Time-Effect Analysis	▪ Six Social Media Experts ▪ Open-Ended, Semi-Structured Interviews

Fig. 2. Approach for quantitatively analyzing the impact of social media management strategies

4.1 Data Collection

The first step of the applied research approach is the collection of the social media data used to evaluate the social media strategies. We started with selecting 100 large global companies from the Fortune 500 list (Fortune, 2012) and made sure that the sample comprised companies from different industry sectors, such as the financial services industry, consumer brands, car manufacturers, IT companies and so on. The primary data for our research was collected from the microblogging platform Twitter. The vast majority of Twitter users distribute information (tweets) publicly that can be collected via Twitter's application programming interfaces (API). The APIs allow us to search and extract tweets as well as metadata. Figure 3 depicts a typical tweet, which is sent from IBM's corporate Twitter account, to illustrate the variety of primary data and metadata that is extractable via the APIs. Especially, the metadata regarding the device or SMM tool used to send the tweet is of interest for our research approach. This allows us to determine the client that has been used to compose a message (e.g., Twitter website, mobile devices, or professional SMM tools).

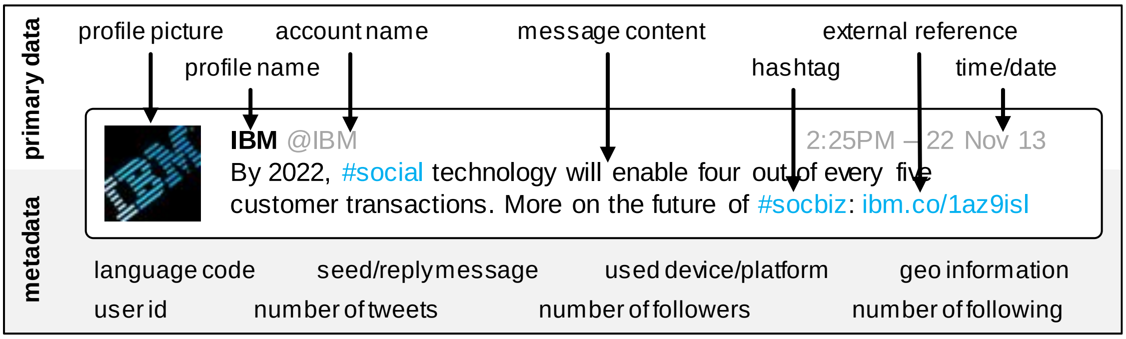

Fig. 3. Primary data and metadata obtainable from a Twitter message

The data collection from Twitter was done using two systems that gathered messages through Twitter's APIs. While the first system gathered all user-generated tweets containing the name of one of the selected 100 companies using the Twitter Streaming API, the second system gathered all tweets sent from the primary corporate Twitter accounts of these companies via the Twitter Search API. In contrast to the Streaming API, the Search API is restricted to 720 queries per hour, which limits the number of accounts that can be monitored without the risk of missing tweets. Therefore, we decided to collect only tweets from each company's primary Twitter account (i.e., the account that represents the company as one entity rather than single services or products). After setting up both systems, we collected the Twitter data automatically between October 2012 and June 2013. The overall database with the collected Twitter messages comprises approximately 38 million user-generated messages and 250,000 company-generated messages. Additionally, we collected secondary data about the companies such as revenue and numbers of employees based on the companies' annual reports from 2012 and the companies' belonging to a certain industry sector was derived from the International Standard Industrial Classification.

4.2 Data Selection

In the second step, we selected the set of companies for the subsequent preprocessing. Eight of the Fortune's top 100 companies were not considered any further as they did not have a Twitter account at all (i.e., Apple or several Chinese companies). Furthermore, several accounts were inactive during our data gathering period so we did not consider them either for further investigation. Finally, we screened the user-generated tweets for each company to test if they could be assigned meaningfully. Companies with ambiguous names (i.e., UPS, or HP) were removed from the data set since it was not possible to automatically detect if the tweets referred to the company or something else. Of these remaining accounts, the 50 companies with the highest public interest based on the number of user-generated tweets were selected for further analysis. After this selection step, the dataset contained over 17 million user-generated tweets and almost 200 thousand tweets sent by companies.

4.3 Cleaning and Preprocessing

The next step comprises the cleaning and preprocessing of the Twitter data for the subsequent regression analysis. Initially, we screened the content of the collected messages for errors (e.g., non-readable characters) and cleaned up the data to improve the data quality for the preprocessing.

Subsequently, we assessed the sentiment of the users' opinions shared on Twitter to determine how positive or negative companies were perceived based on word of mouth. For this task we deployed an automated unsupervised sentiment analysis to handle the large amount of data that allowed for determining "... positive and negative opinions, emotions, and evaluations ..." (Wilson et al., 2005, p. 347). A sentiment analysis processes data in two consecutive steps: first, it assesses whether a message contains subjective statements before it classifies the sentiment of the message to be positive or negative (Liu, 2010). We used the publicly available tool "SentiStrength 2", developed by Thelwall et al. (2012). It is especially designed to analyze the sentiment of short informal texts like those that can be found on Twitter and which accounts for a variety of grammatically wrong but in social media often used forms of writing. The SentiStrength algorithm returns a sentiment assessment ranging from -5 to +5 for every message expressing their tonality. The algorithm is based on a dictionary approach which analyzes messages based on a list comprising predefined words that signal subjectivity (Wilson et al., 2005; Liu, 2010). The applied word list is an adjusted version of the dictionary of the General Inquirer (2012) based on human polarity and strength judgments comprising more than 2,500 English words and radicals signaling emotions in text (Thelwall et al., 2012). Because the setting of the sentiment analysis only allows for analyzing messages written in English we applied a language detection algorithm to identify messages that were written in English. Thereby, we were able to increase our data set by not only investigating messages with the metadata language code for English, but also those tweets shared in non-English speaking countries which were also composed in English. The applied algorithm uses a naïve Bayesian filter based on language profiles generated from Wikipedia abstracts. As result, we were able to increase the data sample of English messages by 10%.

4.4 Transformation

In the following step we transformed our dataset into independent, dependent and control variables to represent the data comprehensively with regard to our research question. As *dependent variables* to analyze the strategic impact of professional corporate SMM tools in contrast to manually handling corporate Twitter accounts using the Twitter web-frontend, we measured user *word of mouth* and *attitudinal loyalty*.

We consider *word of mouth* based on the sentiment of the user-generated content (e.g., opinions and recommendations) for each company (Chen et al., 2011) in terms of the general average daily sentiment (DV_1) and the more specific daily relative frequencies of positive (DV_2), negative (DV_3), ambivalent (DV_4), and neutral (DV_5) tweets. DV_1 comprises the mean sentiment of all tweets per day while DV_2, DV_3, and DV_5 posit the number of tweets with a positive, negative, or no sentiment score relative to all user-generated tweets per day. Ambivalent tweets (DV_4) contain positive and negative sentiments whose polarity in total added up to zero. The other dependent variable *attitudinal loyalty* is conceptualized through user involvement (DV_6) and relationship strength (DV_7). Thereby, we assume that the more a user is involved with the company, the more he or she will communicate about it. Accordingly, for user involvement (DV_6) we divided the total number of messages by the total number of users sending a tweet about the company. Finally, the number of followers indicates how well a company is connected with the users who voluntarily demonstrate their affinity with the company (Clark and Melancon, 2013). For the companies' estimate for its relationship strength (DV_7) with the community, we used the number of followers as a proxy.

The *independent variable social media management strategy* relates to which Twitter management approach a company adopted to send tweets. The two SMM *strategies* that can be observed are either using the Twitter web-frontend for sending tweets or applying a professional SMM tool. In addition, we investigated separately a strategy change (i.e., companies switched from web-frontend to an SMM tool during the period of investigation). From an operational point of view, we counted the number of tweets for each company sent via the Twitter web-frontend (*Web*), via any professional *SMM* tool or via other channels (e.g., mobile devices or external sources like Instagram or Tumblr). Based on the relative frequencies of each channel, companies that sent the majority of their tweets (more than 60%) via the Web or SMM tool were classified accordingly.

Table 1
Descriptive statistics for the analyzed social media strategy groups.

Social Media Strategy	**N**	**Company-generated Tweets**						**Average Number of Company Tweets**	**Average Number of User Tweets per day**
		[relative frequency]			[absolute frequency]				
		Web	SMM	Other	Web	SMM	Other		
Web	11	80.79	12.17	7.04	971.27	187.18	74.44	1224.09	976.50
SMM	26	10.13	82.05	7.82	236.04	4727.36	129.15	5087.27	998.47
Change	8	51.42	31.28	17.3	934.5	510.25	135.38	1760.16	977.47

Social Media Strategy	**Control Variables**								
	CV_1 Revenue [$bn]	*CV_2* Employees	*CV_3* Industry Sector						
			C	D	G	H	I	J	K
Web	133.979	140,466	2	2	1	1	0	2	3
SMM	6174.347	313,024	10	1	2	1	1	8	3
Change	149.799	234,835	2	1	0	0	1	3	1

Notes: Company-generated Tweets refers to the average total number of company Tweets within the respective strategy group.

Furthermore, we incorporated *change in strategy* to acknowledge the companies that have switched from Web- to SMM-based tweeting during our data collection period. In order to determine whether a company switched its SMM strategy and at which point in time, we conducted a Receiver-Operating-Characteristic (ROC) analysis. For this purpose, we compared the distributions of the frequencies of Web- and SMM-based tweets over time within each company. We then computed the *Youden Index (J)*, a common *ROC* summary measure, to determine empirically whether both distributions (Web and SMM) can be sufficiently separated from each other (over time) and where the switching point between Web- and SMM-based tweeting lies. The index ranges between 0 and 1, with values close to 1 indicating that both distributions can be clearly distinguished and values close to 0 indicating congruent and indistinguishable distributions (Youden, 1950; Schisterman and Perkins, 2007). In case there was a change in strategy, the time when a company switched from Web to SMM was determined by the *J* corresponding optimal cutoff-point (Schisterman and Perkins, 2007). We performed a non-parametric *ROC* analysis for the 18 companies that sent at least 50 tweets via each platform (Metz, 1978). Eight companies with a sufficiently high level of separability ($J \geq .6$) were classified as changing strategy companies (Fluss et al., 2005). Ultimately, two out of the 50 companies were excluded due to incomparably low company-generated tweet numbers (less than 100) and three more companies were dropped from the analysis, as they did not pursue a SMM strategy according to our understanding (either more than 60% platform specific tweets or a clear strategy change with $J \geq .6$).

Table 1 displays the descriptive statistics in company and user generated tweets as well as the control variables that characterize the companies pursuing the different SMM strategies.

As *control variables* we incorporated company revenue (*CV_1*), employee numbers (*CV_2*), and belonging to a certain industry sector (*CV_3*) in our analysis. This enabled us to control for contortions due to industry specific company-user interactions (i.e., companies with strong retail brands might have a stronger need for customer relationship management and thus SMM than companies belonging to the manufacturing or chemical industries sector). Since it is reasonable to assume that larger companies are more present in the public's perception than smaller companies, we controlled for employee numbers to account for company size related effects. In order to control for enterprise performance influences, we also considered a company's annual revenue as a possible bias.

4.5 Data Analysis and Results

Our initial analytical step was to provide first evidence for the general effectiveness of professional SMM tools and to answer our research question of *how companies can influence their perception among social media users*. Thus, we compared the SMM and Web using companies concerning their word of mouth and attitudinal loyalty. The a-priori MANOVA revealed significant differences between the two groups regarding the dependent variables in general ($F_{6,30}=2.346$, $p<.05$, $\eta p^2=.319$). To analyze more detailed group specific differences between the two SMM strategies, we conducted a post-hoc (see Table 2) analysis using Games-Howell tests for the average sentiment and the follower score because of variance heterogeneity ($F_{1,35}=5.409$, $p<.05$; $F_{1,35}=7.257$, $p<.01$), while the other dependent variables without violation of variance homogeneity were tested with Tukey-Kramer tests (Creswell, 2013). The analysis revealed that companies applying professional SMM tools have a significantly better word of mouth compared with companies that limit themselves to web-based use of Twitter ($\bar{x}_{1,1}=0.06$, $\bar{x}_{1,2}=0.152$ $T=-2.031$, $p<.05$). This can – more specifically – be attributed to the fact that users communicate more often positively ($\bar{x}_{2,1}=28.8$, $\bar{x}_{2,2}=33.1$ $T=-2.082$, $p<.05$) and less often negatively ($\bar{x}_{3,1}=22.38$, $\bar{x}_{3,2}=18.91$ $T=2.213$, $p<.05$) about the company while the share of neutral and ambivalent messages is not influenced by SMM tools. Concerning the user's attitudinal loyalty towards the companies, we found a superiority of SMM in relationship strength ($\bar{x}_{7,1}=58901.64$, $\bar{x}_{7,2}=590845.65$ $T=-2.212$, $p<.05$) but not in the user involvement ($\bar{x}_{6,1}=1.2$, $\bar{x}_{6,2}=1.24$ $T=-0.598$, $p>.05$).

Table 2

Groupwise comparison of companies with different social media management strategies.

Dependent Variable	***Social Media Strategy***				**df**	**T**	**p**
	Web		**SMM**				
	$\bar{x}_1$	**(SD)**	**$\bar{x}_2$**	**(SD)**			
Word of Mouth							
DV_1: Avg_Sentiment	0.06	(0.18)	0.152	(0.11)	13.047	-2.031	$<.05^*$
DV_2: Positive_Sent	28.8	(7.24)	33.1	(4.95)	35	-2.082	$<.05^*$
DV_3: Negative_Sent	22.38	(5.59)	18.91	(3.78)	35	2.213	$<.05^*$
DV_4: Ambivalent_Sent	5.93	(1.29)	5.95	(1.29)	35	-0.024	$>.05_{n.s.}$
DV_5: Neutral_Sent	42.97	(4.63)	42.07	(6.45)	35	0.372	$>.05_{n.s.}$
Attitudinal Loyalty							
DV_6: Involvement	1.2	(0.186)	1.24	(0.156)	35	-0.598	$>.05_{n.s.}$

DV_7: Relat. Strength	58901.6	(94540.1)	590845.6	(1217760.7)	25.704	-2.212	<.05*
Statistics: x̄ = group mean; SD = standard deviation; df = degrees of freedom; **p-values:** * p < 0.05; n.s.= non-significant (two-tailed significance test)							

We controlled for effects of the company revenue (*CV_1*), number of employees (*CV_2*) and industry sector (*CV_3*) by comparing the Web and SMM groups with additional Tukey-Kramer (*CV_1*, *CV_2*) and Mc-Nemar tests (*CV_3*) (Creswell, 2013). The results showed no differences between groups in revenue ($F_{2,42}$= 0.726, p >.1), employees ($F_{2,42}$= 0.701, p >.1) and industry (χ^2_{12}= 8.291, p >.1) which negates confounding effects. Furthermore, a one factor ANOVA between the groups did not show any significant difference in the average number of corporate tweets ($F_{2,42}$= 0.448, p >.1). This shows that the companies following a professional SMM strategy do not simply send more Tweets but engage more efficiently with the users to improve their organizational impression management.

Table 3
Descriptive statistics for dependent variables before and after the SMM strategy change.

SMM Strategy Change	N		Dependent Variables						
	Days	Weeks	DV_1	DV_2	DV_3	DV_4	DV_5	DV_6	DV_7
Web (Pre-Change)	1336	191	0.217	33.82	15.64	5.07	45.47	1.22	33445.15
SMM (Post-Change)	848	105	0.169	33.16	17.52	5.81	43.52	1.15	58341.28
DV_1 = Average Sentiment; DV_2 = Positive Sentiment; DV_3 = Negative Sentiment; DV_4 = Ambivalent Sentiment; DV_5 = Neutral Sentiment; DV_6= Involvement; DV_7 = Relationship Strength									

To substantiate the internal validity of our findings we considered the randomly time-variant change from Web- to SMM-based tweeting as a natural experiment (DiNardo, 2008). Applying a fixed effects panel regression (Hamilton, 1994) we compared the different word of mouth and attitudinal loyalty scores before and after the introduction of a SMM tool for the eight companies in the *strategy change* group. For this purpose, we dummy coded the strategies with pre-change web-based tweeting as reference category. This approach enabled us to control for (1) any invariant a-priori idiosyncratic differences among the companies (i.e., revenue, number of employees, and industry) through the restricted fixed effects assumption, (2) for a temporal linear trend (*trend*) and (3) the (dummy coded) day specific changes (which are not displayed in the tables for the sake of clarity) additionally to the consideration of the focal effect of the social media strategy change (*change)* (Wooldridge, 2009). The underlying descriptive statistics in the dependent variable measures and the average number of days and weeks before and after the strategy change is illustrated in Table 3.

The panel regression generally supports our previous findings while it also provides further unexpected insights. We found a highly significant increase in relationship strength ($\bar{x}_{7,1}$=33445.15, $\bar{x}_{7,2}$=58341.28, T=7.25, p<.001) within the first months following the strategy change. Unexpected yet not unreasonable, the introduction of a professional SMM tool caused a significant increase in messages with a negative sentiment ($\bar{x}_{3,1}$=15.64, $\bar{x}_{3,2}$=17.52, T=-2.0 , p<.05). The implementation of a more active SMM strategy triggers people to send more negative messages within the first months after the strategy change (see Table 4). The other dependent variables did not vary significantly before and after the change from Web- to SMM-based tweeting.

Table 4
Fixed effects panel regression in negative sentiment and relationship strength before and after the SMM strategy change.

SMM Strategy Change	DV_3: Negative Sentiment					
	Regression Coefficient	T	p	SE	Collinearity	
					VIF	Tol.
Const.	-1.24	-1.06	$>.05_{n.s.}$	1.17	1.02	0.98
Trend	0.00003	1.20	$>.05_{n.s.}$	0.00003		
Change	-0.011	-2.05	$< .05^{*}$	0.006		
	$F_{209,1454} = 1.16$, $p <.08^{\dagger}$, $R^2_{within} = 0.1424$					
SMM Strategy Change	**DV_7: Relationship Strength**					
	Regression Coefficient	**T**	**p**	**SE**	**Collinearity**	
					VIF	**Tol.**
Const.	-3210545	-21.49	$<.001^{**}$	149381	1.02	0.98
Trend	78.73	21.75	$<.001^{**}$	3.62		
Change	5155.06	7.25	$<.001^{**}$	710.68		
	$F_{273,1359} = 6.14$, $p <.001^{**}$, $R^2_{within} = 0.5522$					

Statistics: SE = Standard error; VIF=Variance Inflation Factor; Tol.= Tolerance; R^2_{within} = percentage of explained variance in DV through changes within predictors
p-values: ** p < 0.001 highly significant; * p < 0.05 significant; † p < 0.08 tendential significance; n.s. p > 0.05 non-significant

4.6 Expert Interviews

Complementary to the quantitative analysis, we conducted open-ended, semi-structured guided tandem interviews with six social media professionals in Denmark, Germany, and the United States. We conducted semi-structured interviews because they allowed us to adapt flexibly to the respondents (e.g., clarify comprehension questions) while guaranteeing a reasonable level of objectivity. In the interviews, we were interested in the social media practices of the companies, the workflow managing social media activities, and the usage of SMM tools in general. The interviewees were responsible for their companies' social media activities in the sports industry (two) and financial sector (three). The companies have been active on social media for about seven to eight years and have on average 40,500 employees, from which on average 37 people are working with social media. Two interviewees pursue a Web-based social media strategy whereas the other three have a SMM-tool in use. The companies are active on social media platforms such as Facebook, Twitter, Instagram, and Youtube but also on platforms that are successful in their countries. Additionally, we interviewed a senior consultant from a social media service provider who supports companies developing their social media engagement strategy and adopting SMM tools. The interviews were conducted over a period of two months, beginning in May 2015. On average, the interviews ranged in length from about 50 minutes to 70 minutes and were conducted by two of the authors. At the beginning of each interview, the research model and the results of the quantitative study were explained to the interviewees. We took extensive notes during the interviews and transcribed the audio files immediately after each interview. The recorded interviews and notes were then used to gain complementary insights into the strategic impact of using a SMM tool and to develop bridging meta-inferences from the mixed methods approach in the next section (Venkatesh et al., 2013).

5. Discussion of the Results

The goal of this study is to provide evidence on how different SMM strategies have an effect on the public perception of social media users. The quantitative analysis showed a positive influence of using a SMM tool-based strategy over a web-based strategy and the effects of changing from a web-based strategy to a SMM strategy. Concerning the underlying effects of SMM tools, the subsequent interviews revealed that companies mostly engage in social media for communication, marketing, human resources or customer care purposes. Each channel may have different target groups which makes it a big challenge to align the social media accounts to serve a common mission. An interviewee explained: ‘The company is forced to be active on new channels that were not planned because customers began talking on these channels about the company. Social media platforms are selected based on their popularity in different countries’. In this context, one interviewee said that ‘a downfall of native front-end devices is that the aligning of accounts and stories is difficult’. Especially when accounts are operated by different persons, a SMM tool that allows management of the work flow makes it easier to provide a consistent image to the public. One respondent presented details on the respective targets of social media activities from a company’s perspective: ‘(1) increase customer satisfaction so that they become advocates for the company, (2) establish trust among the users to improve the sentiment, and (3) generate measurable results regarding engagement or marketing campaigns’. The respondent added: ‘The social media strategy has to support the overall business strategy’. Social media is not used in a company to serve social media goals as an end in themselves that might be independent of the business strategy. Another expert explained that the social media channels are used to make good impressions about the company. Overall, the introduction of a SMM tool depends on its business value for the companies. In this regard, a SMM strategy enables different company divisions to bundle strengths to collectively support the general business strategy across the managed social media platforms.

Considering impacts on the organizations’ public perception, the interviews generally show that SMM tools support the individual work flow and work practices of the employees involved. The respondents described how they are able to handle user requests with the SMM tool by identifying all inquiries, assigning them to a qualified employee and keep track of the solution. One interviewee stated that: ‘After adopting a SMM tool the number of dialogs with users where the sentiment changed from negative to positive over the course of the dialog increased’. This is due to the fact that the SMM tools help companies to better understand the users and also provide background information for handling a request. Another respondent added: ‘The SMM tool also provides information about the previous communication with a user’. One of the experts elaborated: ‘It is possible to slip in into conversations like a regular user’. This increases empathy with the users and requests can be faster processed’. Another expert pointed towards the supportive function of SMM tools: ‘The employees are generally already trained in communication skills. The trainings only teach them to properly use the tools to support their work’. The results of the quantitative analysis support the statements of the interviewees and provide evidence for an increase in the average word of mouth for companies actively managing their public perception with SMM tools. This can be attributed to the 4.3 percent point increase in positive user-generated tweets and the 3.5 percent point decrease in negative tweets.

Furthermore, we were able to identify a significant increase in user attitudinal loyalty in terms of relationship strength as a result of active SMM. Moreover, the interviewees stressed the importance of providing content that is relevant for their stakeholders. One interviewee explained that focusing on the target groups regarding social media activities and content has had the highest return on reputation for the company. Therefore, analyzing the social media environment using a SMM tool helps to provide users with the relevant content and to ultimately increase attitudinal loyalty. One respondent explained: 'Not everything needs to go viral. Sometimes it is important that a message resonates with other stakeholders'. Thus, we see that the application of SMM tools supports the companies' engagement with customers which improves their public perception.

Regarding the analytical insights into the social networks, pursuing a professionalized social media tool-based strategy allows companies to monitor social media activities. In line with one response of an interview, 'The internal standard is to contribute not for the sake of posting content, but to provide great content to the audience', our quantitative findings show that regardless of the applied strategy there are no differences in how many messages the companies share on social media. The SMM tools provide information used to monitor the activities on social media like the sentiment of the messages, the reach of messages, and the success of campaigns. Based on the responses of the interviewees, we see that SMM tools enable companies to be more efficient in their social media activities. Companies can use different key performance indicators (KPIs) to measure the effect of their publishing (e.g., marketing, human resources) and engagement (customer care) activities. One interviewee explained: 'We are measuring KPIs like the answering time and the manually determined sentiment'. This information can subsequently be used to select the appropriate organizational impression management tactics and actions to make targeted impressions (Mohamed et al., 1999).

Overall, the quantitative analysis supports our findings that the strategic use of SMM tools on behalf of the companies improves their word of mouth among the social media users and helps to build stronger relationships with the user community. If the usage of tools is fragmented in a company, the information flow is hindered and assigning tasks and implementing routines and processes is difficult. One interviewee described the usefulness of information sharing between departments over a SMM tool: 'The tool allows informing other departments about identified influencers'. Two interviewees explained that companies engaging in social media will come to a certain level of professionalization when they need to adopt a SMM tool in order to climb the maturity ladder further. A respondent stated: 'The pressure on companies to align all their social media channels is increasing and it is important to enable the information flow between the social media workers'.

Introducing a SMM tool confronts companies with different challenges they have to cope with to be successful. The interviewees using a SMM tool explained that a strategic business case was needed to justify the adoption of the SMM tool. One of the respondents, whose company pursues a Web-based strategy, stated: 'Getting funding for a professional SMM tool is definitely a major issue'. One interviewee explained that with the introduction of the SMM tool 'there was no increase in budget or new people hired. However, employees were trained to work with the SMM tool to use it adequately and efficiently'. Hence, the expected benefits of introducing a SMM tool are to gain the ability 'to manage the work on social media' and to 'gain access to competencies of the SMM tool vendor'. We investigated the immediate effects of a strategy change from Web-based to SMM-tool-based tweeting. Our findings substantiated our hypothesized increase of relationship strength through the use of a SMM tool. Concerning word of mouth, we found an increase in negative messages following the introduction of a SMM tool which, however, does not impair a company's overall word of mouth. The unexpected non-significant difference in the average sentiment and the positive sentiment can be attributed to the short period of time that the companies had to deploy the full strength of the SMM tools and to overcome the aforementioned initial negativity bias. It is reasonable to assume that improving the overall word of mouth and getting users to actually speak up for a company takes more time and effort. One respondent summarized the biggest challenges of introducing a SMM tool are discrepancies in the expectations between the customer and the tool-provider, the continuously changing social media environment, and an unrealistic self-evaluation of the customer regarding their maturity of social media experiences. The time dependent analysis of switching to an active social media impression management strategy shows that it is important for companies to consider and address an initial negativity bias. We found an assimilation gap in public perception benefits during the initial phase of SMM adoption. Such assimilation gaps are common when deploying new information technology (Fichman and Kemerer, 1999). Overall, the results show that within the first five months the more active SMM leads to an increase in relationship strength with the social media users who tend to speak more critically about a company. This initial negativity bias, however, does not affect the company's overall word of mouth. On the contrary, active impression management in form of a SMM strategy leads to a general improvement in the average user word of mouth as people communicate more positively about a company. This is also the experience of one interviewee who stated that: 'User sentiment got more positive as inquiries of users are addressed more timely'.

As a last point, the interviewees stated the most important benefits of using a SMM tool. In summary, it can be concluded that SMM tools make processes regarding social media consistent and transparent. Consistency deals with how different social media accounts and platforms can be handled in a company to make uniform impressions in favor of the company. Transparency addresses the fact that the SMM tools make actions more comprehensible and allows monitoring of their success. This in turn allows companies to set-up data-driven processes and to make informed decisions.

6. Conclusion

This study was motivated by the increasing usage of social media platforms in an organizational environment. We analyzed a large amount of social media data to investigate our research question and enhanced the quantitative analysis by gaining further insights through interviews. We provide first evidence for the efficacy of strategic SMM on the public perception of social media users to support organizational impression management. In this regard, SMM tools seem to have a catalyzing effect on the work of employees by providing the communicatively well-trained workers with additional insights about the users and enhance their efficacy when engaging with users. Not taking social media engagement seriously can cause a negative impact on companies' perception. In this regard, companies are increasingly confronted with firestorms on social media or the publication of hoaxes. Even though such events may be triggered by a small number of users they can spread fast through the digitized stream of messages (Dellarocas, 2003).

6.1 Theoretical Contribution

Our work contributes substantially to the few existing studies on managing social media at the organizational level and sheds light on how companies can develop their social media capabilities (Miller and Tucker, 2013). Thereby, we answer the call from Aral et al. (2013) who are requesting more research on strategies and tactics that companies can deploy to engage in social media. In this regard, we provide evidence for the strategic value of applying a professional social media strategy by using SMM tools. Overall we conclude that SMM tools enable a company to not only engage in social media but also monitor the activities on these platforms. We contribute to the growing literature on organizational impression management presenting how professional social media management supports companies to influence the public perception in social media (Schniederjans et al., 2013). Thereby, we conceptualize and measure public perception based on concepts from marketing research – word of mouth and attitudinal loyalty. Based on the usage of SMM tools, companies can better understand the needs of their customers and stakeholders. We are able to show that SMM tools help companies to execute organizational impression management to present themselves in a positive way to the public. Thereby companies are able to build stronger relationships with potential customers, and improve their word of mouth. Methodologically, we contribute to the literature by combining quantitative and qualitative research in a mixed methods approach based on the guidelines from Ågerfalk (2013) and Venkatesh et al. (2013). We present how outcomes from big data analytics in the area of social media can be enriched by qualitative research to better interpret the results. Moreover, we contribute to the literature by applying the knowledge discovery process of Fayyad et al. (1996) from the area of information science. We show how the steps of this process can be applied in social media research where increasingly large datasets need to be managed.

6.2 Practical Implications

The study also provides profound implications for companies that are evaluating or setting-up their SMM strategy whether by applying a SMM tool or using a SMPs web-frontend. We provide a detailed description of how to collect and analyze Twitter data mostly automated with open source applications in order to monitor their own public perception. Thereby, companies can track the development of users' loyalty, the sentiment of the public discussion and the discussed topics in social media messages. SMM tools provide monitoring functionalities for early warning to address issues swiftly and effectively. In bad events, companies can make use of their loyal users to evoke countermovement. Moreover, if a company is not able to monitor the effectiveness of their social media engagement, its social media strategy cannot be appropriately adjusted to recent developments in social media and desired outcomes may not be achieved. Furthermore, companies can use this approach for competitor analysis to identify based on tweets of and about competitors which social media strategy they apply, which tools they are using as well as how they are perceived by the public. Thereby, companies can assess strengths and weaknesses of competitors' social media engagement and leverage this knowledge to improve their own strategy. However, companies need to be aware that SMPs such as Twitter or Facebook increasingly limit the free access to their data. Instead, they rely more and more on data resellers (e.g., DataSift and Gnip) and social media analytics firms (e.g., Hootsuite and Salesforce) which help companies to monitor and manage social media. Paid access to social media data offers an increased set of information with high volume and at a higher speed, even in real-time. Hence, companies have to make decisions about the richness of the data required to satisfy their information demand. Such decision has to be independent from whether a company is active in social media as users contribute information about a company regardless of the company's engagement.

6.3 Limitations and Future Research

The limitations of our study are based on the conceptualization of our research model as well as the setup of the quantitative and qualitative research approach. A limitation arises based on our conceptualization of SMM strategy based on the deployment of SMM tools as an indicator. Hence, the quantitative analysis does not consider changes in processes, organization or human resources related to the adoption of an SMM tool. We addressed this limitation in our study by conducting additional interviews in a mixed methods approach to shed light on what accompanies the use of a SMM tool at a company. However, future research should broaden out the conceptualization of SMM strategy following the work of Chen et al. (2010) and their conceptions of IS strategy. We also have to comment on the operationalization of our variables. Although we draw on findings in the field of social media research to construct the variables, there might be other metrics eligible to measure the proposed variables. In our study, involvement, measured by the number of tweets per user, is found to be non-significant. Future research should address this limitation by constructing involvement in a different way (e.g., based on how often users 'like' content of a company), depending on the methodology used in future studies.

Regarding the quantitative study, it needs to be acknowledged that our findings are only representative for the analyzed SMP Twitter. Although no findings actually demonstrate a different effectiveness of Twitter, other platforms like Facebook might have different strengths and weaknesses that need to be considered (e.g., information sharing, innovation creation, marketing). Furthermore, the results might be influenced through a sample bias because we analyzed companies that are very active on Twitter independent from web- or SMM-based tweeting. This might be also the reason for the rather low frequency of negative messages we observed, although negative messages travel fast on social media compared to positive ones (Dellarocas, 2003). Approximately 30% of the messages in our dataset are positive and 20% are negative. That might cause an underestimation of the actual SMM effect, as the general word of mouth level is above average. We considered large global companies that are already subject to a considerable share of public perception. Thus, all of the companies in our sample are somewhat experienced in managing their impression on Twitter. Future research is needed to investigate other companies deploying SMM tools without success. Inspecting the initially excluded companies in our sample however, we find that the ratio of SMM companies decreases (by approx. 8%) while Web companies increases (by approx. 5%). Thus, indicating that an increase in public perception is associated with a SMM strategy while a decrease in public perception correlates with Web strategy. The applied dictionary of the sentiment analysis only allowed processing of tweets in English. We accounted for this limitation through additional language detection, which ensures that tweets are not limited to English speaking countries. Nonetheless, although English is often used on Twitter by non-native speakers, an underrepresentation of non-English speaking countries was unavoidable.

Since we conducted a mixed methods approach, additional deliberations particularly regarding the study's meta-inferences need to be considered. Generally, one needs to consider potential threats to validity that could arise during data collection and analysis (Venkatesh et al., 2013). Unconscious interviewer biases (e.g., through the young age or male sex) are genuinely possible and difficult to explicitly prevent. These aspects might have promoted particularly venturesome statements or an overemphasis of one's own success. However, we controlled for common conscious interviewer distortions of the respondents' reaction possibilities in the form of the reduction of the response times by standardizing the interview length. Considering, that the age and organizational position of the respondents varied greatly, we expect interviewer effects of the social distance (e.g., lack of trust) to be unsystematic and negligible. The interview situation is known to potentially affect the interview responses as well. We generally tried to reduce these effects (e.g., of uncertainty or unfamiliarity) by conducting the interviews in the habitual environment of their own office. Comparable to the sample bias in the empirical study, it is possible that the interview respondents were only willing to voluntarily participate in our study because they might have felt they were examples for especially successful social media management or are particularly interested in this topic. Since this, however, would pertain to respondents of all different SMM strategies, we argue that this actually increases the compatibility of samples and consequently the meta-inferences' integrative efficacy while impairing the inference transferability. Also, one needs to consider biasing effects through the formulation of questions e.g., by asking leading questions. We addressed this potential issue through orienting ourselves by the pre-formulated questions and providing sufficient time to properly prepare the next question by alternating the conversation conduction between interviewers. Lastly, we find the value of the integrative correspondence of the study's meta-inferences to be profound. We pursued a complementary purpose through the mixed methods approach by seeking the substantiating mechanisms underlying the empirical observations. In this regard, the interviews provide sound explanations corresponding with the quantitative results.

Our study provides additional links for future research. Future research, should address which aspects of the SMM tools (i.e., more frequent information sharing, user-specific interactions, and instant reactions) are the underlying reasons for the significant difference to the Web-based social media approach. In addition to that, future research should pay attention to how companies can integrate SMM into their existing decision support systems and how companies build up capabilities for understanding social media activities. Furthermore, we limited our analysis to attitudinal loyalty and word of mouth. Further analysis should also consider additional social media metrics and variables such as user satisfaction or the return on investment to determine the success of social media strategies.

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