Effectiveness of Corporate Social Media Activities to Increase Relational Outcomes

Abstract

This study applies social media analytics to investigate the impact of different corporate social media activities on user word of mouth and attitudinal loyalty. We conduct a multilevel analysis of approximately five million tweets regarding the main Twitter accounts of 28 large global companies. Thereby, we empirically identify different social media activities in terms of social media management strategies (using social media management tools or the web-frontend client), account types (broadcasting or receiving information), and communicative approaches (conversational or disseminative). We find positive effects of social media management tools, broadcasting accounts, and conversational communication on the public perception.

Keywords: Social Media Management Strategy; Social Media Analytics; Corporate Social Media Management; Word of Mouth; Attitudinal Loyalty; Twitter.

Introduction

Over the past decade, social media platforms such as Twitter or Facebook have experienced an unprecedented growth in user numbers, which subsequently caused a proliferation of data in form of information, opinions, and relations [63]. Social media analytics has used this data for multiple purposes such as predicting elections [103] or stock market developments [11], product design [18] and brand communication [44]. Companies use social media in general and microblogging in particular for different purposes such as market research, recruiting, public relations, and reputation management [48, 112]. The underlying commonality of social media activities, however, is to improve and exploit user relationships [97]. Successfully addressing these purposes requires effective social media management strategies to include both a social media analytics enabled monitoring of the public data stream as well as the active participation through interaction. To do so, companies increasingly rely on social media management tools (SMMT) to gain insights in the brand perception among users, detect trending topics, or monitor competitors [29]. For example, the New York Stock Exchange applies SMMTs to provide investors with real-time information about trade-related public sentiment [76], Apple acquired a social media analytics provider for $200 million [104], and Twitter itself has bought the data reseller GNIP causing an eleven percent increase in Twitter share price [93].

With the growing commercial relevance of social media, researchers have begun to investigate the influence of social media management and corporate Twitter accounts on relational outcomes. Evidence has been found that social media indeed is capable to increase relational outcomes such as online reputation and relationship strength [22, 61, 71]. However, more research is needed since we still lack a deeper understanding regarding the impact and relation of different social media management strategies on relational outcomes. In the case of Twitter, companies can follow two different primary engagement approaches to manage their social media appearance: Like every other user they can either use the web-frontend to manually enter messages through their corporate account and monitor user interactions. Alternatively, they can apply more sophisticated, professional SMMTs, which provide additional social media analytics features to monitor interactions, sentiments, or trends in real-time that support corporate relationship management. Apart from the social media management strategy, social media analytics research has identified different user account characteristics (e.g., status or friends) and message content features (e.g., sentiment or directed mentioning) to affect the public awareness [66].

Until today, however, there is only limited research that provides insights into the efficacy of different social media management strategies, account types or communicative approaches to attain relational outcomes and how to appropriately measure success on social media [5, 29, 47]. Prior research has been concentrated on reactive self-report measures instead of analyzing the actual behavior on Twitter [22] and did not distinguish different ways of managing corporate Twitter activities such as comparing different social media management strategies [71], or simply looked at results of social media management (i.e. relationship depth, engagement or corporate reputation) without consideration of the underlying factors on multiple outcome variables [61]. However, practitioners and researchers alike hold great interest in drawing valid inferences from social data and translating these insights into action [74, 97]. Accordingly, Aral, Dellarocas and Godes [5] call for more research on how organizations can successfully interact with social media platforms, which social media strategies companies should pursue, and how to measure outcomes of social media for companies. Moreover, Stieglitz, Dang-Xuan, Bruns and Neuberger [97] specifically propose to determine how social media analytics can support firms in their community management activities and Pentina, Zhang and Basmanova [82] state that developing distinctive strategies for effectively targeting and engaging users on each platform remains a work-in-progress. In this study, we address this gap by investigating how different social media management activities affect the building of relational outcomes.

We draw on literature from relationship marketing to identify conceptually relevant outcome measures and apply findings from content and diffusion network analysis to derive general account and communication patterns that influence the companies' public brand image. Generally, the goal of relationship marketing is to build loyal customers who advocate for a company and its products. In line with other research, we understand different social media management activities as differing levels of relationship investment that indicate the goodwill of a company to pursue a meaningful relationship with the user which in turn increases relational and financial outcomes [22, 79]. The relational outcomes we investigate encompass customer focused dimensions in terms of word of mouth and attitudinal loyalty [78]. Thereby, we assume a multilevel perspective to respect the complexity of the different social media management activities in terms of social media management strategy, context characteristics, and content features. To address our research question empirically, we apply a hierarchical linear model (HLM) regression approach to analyze approximately 5 million user- and company-generated tweets containing information about the 28 most intensely Twitter-using companies from the Fortune 100 list, which we collected from Twitter at the end of 2013.

The remainder of this paper is structured as follows: After the introduction, we elaborate on our multilevel research model by drawing on extant literature dealing with relevant relational outcomes and corporate social media management in form of strategy, account types and communicative approaches. Thereafter, we explicate our empirical research approach in detail. Subsequently, we discuss our findings 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.

Theoretical Background

Following the framework for social media research from Aral, Dellarocas and Godes [5], we distinguish and analyze corporate social media management activities on different hierarchical levels. Focusing on the interaction between firms and users, we regard relationship marketing as an intermediary process by which the firms try to stimulate the user-to-user exchange and ultimately build brand-centric communities [60]. Specifically, we assume that the company's relational outcomes on social media is a result of the message characteristics immediately apparent during the interaction (content features) and – on a higher structural level – of a company's overall social media management strategy and the manageable account characteristics. While some related social media analytics research has been conducted on the content and context aspects [e.g., 66, 105], there is a need for more research on the strategic use of social media by companies [5]. For instance, recent findings demonstrate the general effectiveness of corporate social media engagement on relational outcomes [22] or provide some advice regarding the communicative behavior of company employees to increase sales [35]. However, so far social media analysis has adopted a single-level research approach by only considering the company-specific engagement characteristics (e.g., the account typology, message characteristics) and thereby commonly neglected higher level factors (e.g., social media management strategies) in their empirical analysis [e.g., 59, 60, 89]. As Figure 1 depicts, we propose a model with a hierarchical structure that recognizes the characteristics of the interactional level (Level-0) in combination with the overarching company-specific strategic management decisions on the company level (Level-1).

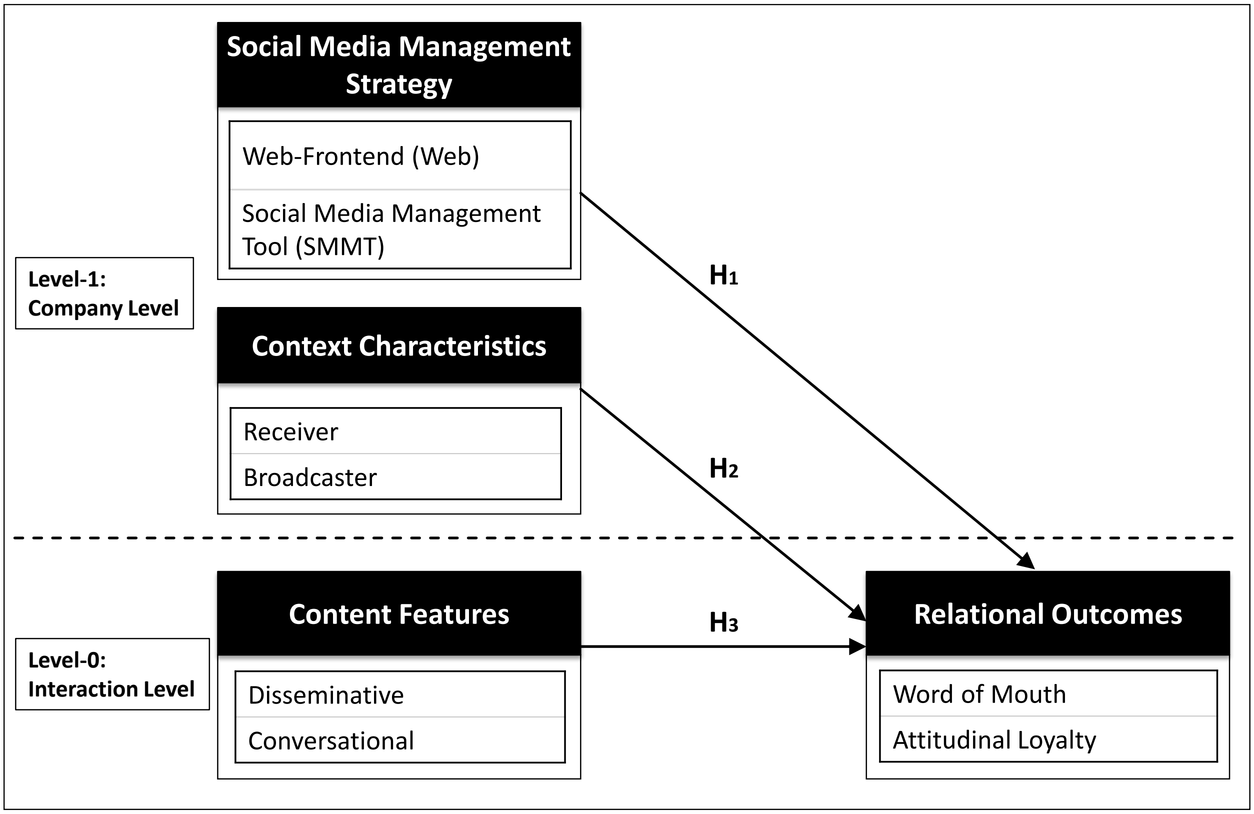


Figure1. Research model for analyzing the efficacy of different social media activities to improve relational outcomes

In this regard, our model overcomes structural shortcomings with respect to the multi-level character of social media engagement with all antecedents conceptualized at an appropriate level. Thus, the model neither aggregates lower level variables to a higher level nor does it assign higher level variables to a lower level. While the former approach excludes meaningful variations at the lower level, the latter does not take into consideration the independence of observations [40]. Including factors on the group level in our model, we therefore apply a hierarchical approach, which allows us to examine the influence of antecedents residing on multiple levels on relational outcomes simultaneously. Accordingly, we argue that relational outcomes in terms of word of mouth and attitudinal loyalty on social media platforms depend on characteristics of the message content on the interactional level as well as on the general social media management strategy and the account characteristics on a company level [74]. Additionally, our HLM-based statistical approach accounts for unobserved heterogeneity on the individual level allowing us to isolate the explanatory power of the proposed characteristics on different levels [85]. Generally, we assume that statistical approaches of social media analytics would benefit from adopting a multi-level perspective for social media research because it addresses common issues of reliability and validity [97]. The underlying theoretical rationale for our hypotheses is developed in the following.

Relational Outcomes of Social Media Management

Relationship marketing has received substantial attention in previous research and, consequently, produced a comprehensive set of antecedents determining the positive outcomes of successful relationship management [91]. Generally, the goal of relationship marketing is to build brand-centric communities with loyal customers who advocate for a company and its products, as well as build oppositional loyalty against competitors' products [22, 60]. These findings support the assumption that relationship investments generate stronger relationships with customers which in turn increase the company performance in terms of sales, market shares, and profits [78]. Recent research indicates that social media has an influence on relational outcomes which means that social media indeed seems to affect the companies' word of mouth, attitudinal loyalty and customer satisfaction which leads to more relational consumers and brand patronage [22, 82]. Drawing upon this research stream, we identified customer focused outcome variables relevant for measuring the impact of different social media management strategies.

In marketing, *word of mouth* is defined as the dissemination of information (e.g., opinions and recommendations) through communication among people. Word of mouth comprises the two key attributes of valence (e.g., positive or negative opinions) and volume (e.g., the amount of information) [21]. Libai, Bolton, Bügel, De Ruyter, Götz, Risselada and Stephen [62] identify the growing connectivity between users via social networking sites as one of the driving factors for the ever-increasing importance of word of mouth. This makes it so important for companies to use social media platforms for managing word of mouth [54, 101]. Specifically, user-generated content contains emotions, opinions, product information, or company perceptions which are spread and disseminated as digitized word of mouth among its users [25]. Considering that emotions are contagious in social situations [94], that users especially tend to spread negative messages about a company [22], that the impact of bad emotions is more persistent [7], and that this increases the importance of reacting rapidly to negative comments [34], it is imperative for companies to actively manage its word of mouth among the users. Vice versa, a greater emotionality towards a brand is key driver for brand awareness [44]. Thus, companies are advised to support positive user word of mouth but also to actively address negative messages to build and improve a stronger brand attachment [94]. Accordingly, in our research we approximate the resultant online-based word of mouth for each company, first, in terms of valence through the share of emotional messages and the average sentiment of the user communication and, second, the word of mouth volume through the overall share of voice.

In general, *loyalty* is seen as the strength of the relationship between an individual's relative attitude and repeat patronage [26] which comprises affective, cognitive and behavioral components [77]. However, research investigating attitudinal as well as behavioral relationship outcomes prevail in relationship studies [108]. Consequently, we consider *attitudinal loyalty* defined as a users' affinity towards a company [22]. In social media, users have the opportunity to display affinity to a brand (e.g., by following or favoring) even when they are not able to demonstrate loyalty by purchasing an organization's products. Around 50% of an organization's Facebook followers are likely to buy their products, and 84% of an organization's Facebook fans are returning customers [22]. In line with previous research, we conceptualize attitudinal loyalty through the user involvement and the relationship quality between user and company [108]. User involvement, in our research, is defined as the user's willingness to make platform specific efforts such as demonstrating a relationship with a company through promoting its messages (in social media analytics literature also referred to as 'brand engagement', see Fan and Gordon [29]). In the case of Twitter, users can express their affinity towards the companies' content through retweeting or favoring the tweets. With the retweeting function, users express a common interest and similarity with the brand within their social network while favoring messages reports the individual's indorsement back to the company. Relationship quality describes the overall strength of a relationship between company and user which is most apparently expressed on Twitter through the follower feature [108]. In marketing, the importance of relationship quality is well established, e.g., as a predictor of repeated purchasing behavior [38].

Social Media Management Supported Relationship Marketing

Within the last decade, social media platforms have massively pervaded the work and private life of users. The two most prominent examples of this development are Facebook and Twitter. The widespread adoption of social media has fundamentally changed the way in which users communicate, collaborate, and consume, which immediately affects the generation and sharing of information [5, 110]. Considering the general goal of relationship marketing to build loyal customers who advocate a company and its products, social media management has proven to be a viable solution for influencing relational outcomes

[22]. Specifically, social media platforms create new opportunities for companies to relate to their customers and for users to interact with each other. In this regard, social media analytics has proven to provide practical solutions for supporting respective corporate marketing activities on social media [97]. Already, most marketers report to use social media for marketing purposes and recent estimates approximate a rapidly increasing worldwide social media advertisement spending of $10 billion for 2013 [22]. Gaining positive effects in firm performance from social media platforms requires companies to develop a successful social media management in terms of interacting with the community and monitoring the user communication [60].

Bar chart:
Displaying the (change in) share of voice of predefined categories.

Pie chart:
Comparison of the share of voice across social media platforms.

Word cloud:
Visualization of frequent terms related to specified keywords.

River of news:
Recent messages on defined topics and source information.

Figure 2. Exemplary overview of a user-interface for a social media management tool.

In this sense, we apprehend social media management as part of a company's general relationship marketing efforts to establish, develop, and maintain a successful relational exchange with the users [22]. By actively engaging on social media platforms companies can build brand-centric user communities which help to gain loyal user advocates, build oppositional loyalty against competitors, and ultimately improve the company performance [10, 100]. However, just creating a social media platform presence on Facebook or Twitter does not automatically lead to better relationship marketing. In order to benefit from social media, companies need to engage in and monitor social media activities themselves to positively influence the public perception of the company [24, 81]. We address this issue in our research by considering a company's general information systems dependent possibilities for engaging on Twitter. Thereby, we differentiate between the primary and secondary social media engagement approaches. For the *primary social media engagement approach*, a company needs to decide whether to principally use the Twitter Web-Frontend Client (*Web*) or acquire a Social Media Management Tool (*SMMT*). The Web-based approach allows to manually send messages via the corporate account like any other platform user. Alternatively, companies can deploy more sophisticated SMMTs (see figure 2) which provide various social media analytics features to support relationship marketing activities in real-time (for an overview see Fan and Gordon [29]). Social media management tools provide an easy solution to obtain high-quality and comprehensive datasets. By accessing multiple social media platforms simultaneously based on predefined keywords, SMMTs address common social media analytics issues like a delayed data access or disparate and complex data access interfaces [97]. Moreover, these SMMTs help to monitor social media conversations about a brand or other keywords and, thereby, enable to draw comparisons between competitors, discover topical trends and measure key metrics regarding the company's online presence. Such tools are developed as enterprise applications and allow handling single social media accounts by multiple users. Moreover, they support user interaction and customer support by identifying key influencers and opinion leaders or managing incoming customer requests [88]. Research has previously elucidated the importance of these features for building brand-centric communities on social media. For example, Kaplan and Haenlein [48] describe the first rule of microblogging being to focus on messages that are relevant for the target group, wherefore companies need to listen before tweeting to find the right balance in the number of tweets sent. Concurrently, Larson and Watson [60] argue that sending customized messages is essential for building brand communities through social media. Another way to efficiently build strong relationships with the users is to focus on information that needs to be reacted upon quickly or to identify and win over the most influential users and thereby leverage the social structure of a social media platform [50]. Generally, SMMT-enabled social media analytics addresses the companies' increasing demand for continuous monitoring of interactions and user-generated content by aggregating, analyzing and visualizing relevant findings [49, 110]. In this sense, proficient interaction monitoring enables to preserve negative customer service exchanges and, thereby, improves customer satisfaction and maybe even prevent potential public relations problems [60].

In this research, secondary social media engagement approaches comprise social media tools which support and complement the aforementioned primary approaches. These approaches either provide specialized engagement and monitoring services or support a more lively social media presence. Among the secondary approaches, we differentiate between *Add-On Social Media Tools* (*Add-Ons*) and *Mobile Device Applications* (*Mobile*). Add-Ons serve different purposes from timing tweets (e.g., Twuffer), over enriching tweets with visual material (e.g., Chute), incorporating topic specific social media comments into a story (e.g., Storify), conducting polls (e.g., Pollowers), and elongating tweets (e.g., Twitlonger) to providing specific services like job postings (e.g., Work For Us). Some of these services also provide selective SMMT-related features that support the monitoring and managing of social media conversations (e.g., Tagboard, TweetDeck, Topicflower). Contributions from mobile devices are commonly sent during events where company members are participating (e.g., exhibition, recruiting event, social commitment) and, thereby, help to make a social media presence more vibrant. Also this provides an opportunity for users participating in the same event to connect with the company. The devices used to send tweets from vary (e.g., smartphones, tablets) as well as the operating systems and the applications (e.g., iOS, Android, Tweetbot, Echofon). So far, it has not been investigated how these supportive engagement approaches have an effect on building brand-centric communities. We refer to the Web and SMMT approaches to be primary, as they determine a company's general social media engagement and have implications for the application of the supportive secondary engagement approaches. For example, a company could decide not to deploy a SMMT in the first place but to compensate for the lack of engagement and monitoring features by deploying various Add-Ons. Thereby, it needs to be mentioned that the social media engagement approaches are not mutually exclusive. While it is likely that one company predominantly applies one primary engagement approach, employees can also use different clients depending on the situational requirements.

From a relationship marketing perspective, the four different engagement approaches correspond with different levels of relationship investment. Relationship investment means a company's investment of time, effort, spending, and resources focused on building a stronger relationship [78]. Moreover, relationship investments indicate the goodwill of a company to pursue a meaningful relationship with the individual which in turn increases user loyalty [79]. In this sense, regarding the primary approaches, applying SMMTs represents a larger amount of relationship investment compared to the simple Web approach because it means that companies are willing to invest money and dedicate employees to manage user concerns. However, distinguishing levels of relational investment for the secondary engagement approaches is more difficult since they do not necessarily require an additional allocation of funds or employees. Nonetheless, it is our understanding that drawing on these supportive approaches shows a strong individual dedication of the employees to present the company more vividly to the users. Generally, a substantial body of research demonstrates the impact of relationship investment on relational outcomes like satisfaction, trust, commitment, and relationship quality [for an overview see 108]. First evidence has been found that an active management of a company's social media presence increases the amount of user-generated content disseminated about it [71], as well as improves the self-reported word of mouth and attitudinal loyalty among users [22]. Thus, also considering the role of different social media management features elaborated above, we generally expect a greater relationship investment in form of a more professional and comprehensive social media management strategy to translate into an improved social media set-up and increased relational outcomes for companies. Thus, considering the different social media analytics features of SMMTs and the established findings from relationship marketing literature, we hypothesize:

Hypothesis$_1$: A higher relationship investment in form of a more professional social media management strategy leads to improved relational outcomes in terms of word of mouth and attitudinal loyalty.

Context Determinants of Relational Outcomes on Twitter

Considering that interpersonal communication proved to be the dominant determinant of perceived relationship investment, companies need to exhibit a high level of interaction skills in order to increase relational outcomes [108]. A growing body of social media analytics literature investigates communication on Twitter based on different characteristics immediately apparent within the message text or contained in the metadata available through the Twitter API [for an overview see 19]. Specifically, content analysis and diffusion network analysis differentiate these metrics into two groups of features, which have been found relevant for influencing the public perception on Twitter. Generally these factors are referred to as (1) context feature or heuristic cues and (2) content features or systematic cues [66, 98].

Context characteristics comprise characteristics of the Twitter account sending the message. Here we consider the account characteristics that companies can immediately manage and which users directly experience when engaging with the company: account verification, amount of messages sent (status), and number of friends. Each of these characteristics has been investigated by extant social media analytics literature. Account verification is seen to express a source's trustworthiness on social media [66]. Generally, trustworthiness describes the extent of perceived source credibility for the receiver [84]. Hereby, users are prone to seek and accept information from a highly trustworthy source since it bears less risk of distortion making it more valuable [16]. On social media, however, assessing a source's credibility is difficult due to the reduced and altered cues environment compelling users to rely on relatively impersonal information from others [17]. In the case of Twitter, companies and users can officially verify their accounts by providing prove for the own identity. After revision, the verification is displayed through a blue check symbol adjacent to the user name. Thereby, companies can establish the authenticity of the account and the credibility of the information as cues for the trustworthiness towards others [66]. In online environments, an account's trustworthiness has been found to improve the publicity of its information [66], raise the perceived value of information [17], and increase the intention to transact with a company [80]. Relationship marketing literature also describes trustworthiness as a key customer-focused relational mediator for attaining relational outcomes [78].

Apart from being followed by others, companies themselves can decide to follow users in return (on Twitter also referred to as 'friends', see Java, Song, Finin and Tseng [45]). Hereby, Twitter has an asymmetric, directed friendship model where users choose other Twitter accounts to follow in their stream but there is neither a technical requirement for reciprocity, nor is there necessarily a social expectation of interaction between users [43, 72]. Thus, friendships can either be reciprocated or one-way [45]. However, by prominently displaying one's number of followers on each person's Twitter page, Twitter creates a quantifiable metric for social status [68]. Thus, by following others, companies contribute to these users' social status who in turn express commitment towards the company by refraining from removing them from their list of followers. Moreover, through the friend feature, network sites enable people to publicly articulate connections and companies to express closeness with their users [14]. Research regarding the effectiveness of relationship marketing has established the importance of these perceived relationship benefits on the formation of close relationships [78]. Accordingly, a larger number of friends on Twitter in turn is associated with more mentionings in other users tweets and a stronger embeddedness in social interaction [72]. Thus, following more users oneself translates into closer relations with the users and an increased awareness within their communication.

The company status refers to the number of tweets sent from the account which is clearly displayed on Twitter amongst the aforementioned context characteristics [98]. The account status is commonly applied as a measure for the activity of a user [72]. In terms of relationship marketing, being more active on Twitter expresses a higher relationship investment from a company since it dedicates more resources towards regular engagement and interaction with the users. Accordingly, a stronger social media activity has been found to improve a company's public awareness in terms of its presence within user communication and the user sentiment towards the brand [22, 71]. Moreover, a source's higher status increases the probability of its messages being redistributed within the network through retweets [67, 83]. As far as relationship strength on social media is concerned, the number of followers was found to increase with the total number of posts as well [43, 58]. It needs to be noted, however, that these beneficial effects of a higher social media activity increase with the account specificity [61].

Regarding the commonalities between the different context characteristics, some research has found a positive correlation between status and friends [58, 72]. Dependent on different context characteristics, Suh, Hong, Pirolli and Chi [98] empirically identify a broadcasting dimension which differentiates accounts based on the number of posts and friends. Accounts with a relatively higher status and more friends are referred to as "Broadcaster" who are associated with a larger number of followers and retweets. In their recent work, Shi, Rui and Whinston [92] also describe social broadcasting on Twitter in reference to the combination of large volumes of information sharing and expansive interpersonal relationships. In this study, we adopt the typology and refer to the alternative type in terms of the semantic opposite as "Receiver" which is characterized by fewer friends and messages. Until today no research has reported results regarding the simultaneous relation between all three characteristics of status, friends and account verification or provided absolute cut-off values for the classification of the different account types. However, seeing that all three characteristics express a larger amount of relationship investment and a stronger appreciation of the social media presence, we expect a positive relation between all three measures. The ultimate empirical identification of Broadcaster and Receiver accounts is based on the relative comparison of companies within the present sample and, therefore, is situation specific for the study context. Regarding the context characteristics we hypothesize:

Hypothesis$_2$: A higher relationship investment in form of a broadcasting account type leads to improved relational outcomes in terms of word of mouth and attitudinal loyalty.

Content Determinants of Relational Outcomes on Twitter

Content features include all aspects of a tweet that are related to its written text. Regarding our content analysis, social media analytics produced considerable insights and metrics for the text classification through text mining concerning the information quality, message sentiment, as well as the communicative approach [for an overview see 1, 3, 57, 65]. Generally, it was found that the information quality contained in a post positively affects its publicity. Hereby, information quality is commonly assessed in terms of the completeness (number of URLs) and amount of information (number of Hashtags) [66, 98, 109, 111]. Considering the brevity of tweets, messages might not contain sufficient information compared to other social media platforms [27]. To enrich information completeness, microblogging users can include a URL to direct audiences towards external webpages for supplementary information [111]. Sharing information through URLs is common practice on Twitter with estimates ranging between 13-28% of tweets providing links to outside content [15, 45, 98]. Additionally, hashtags are clickable links consisting of a keyword preceded by a character "#" to facilitate the topic specific search of tweets [15]. While the use of hashtags can serve multiple purposes (e.g., increase awareness for a topic through assembling messages, emphasize the sender's viewpoint or contribute specific information to a targeted topic), it generally provides supplementary information on the context of the tweet and thereby enhances its comprehensibility [102]. Within the microblogging environment, this seems especially important considering the length constraint and the containing of at least one hashtag in over 10% of tweets [98].

Moreover, the public attention of a message has been found to be affected through its sentiment in terms of the emotional expression [111]. So far, the pattern of findings seems ambiguous regarding the form (positive or negative sentiment) and the degree (presence or absence of sentiment) of the emotionality. On the one hand, Liu, Liu and Li [66] found an increased objectivity in terms of the absence of emotions to increase the retweet probability of a message. On the other hand, a substantial body of research shows that a high degree of affectiveness helps to magnify the vividness of an information, make the position of the sources seem more extreme, and ultimately arouse greater interest [for an overview see 111]. Regarding the form of the emotion, tweets from the news segment with a negative sentiment are predominantly propagated, for non-news tweets positive sentiment enhances propagation [36, 66, 73]. The focus of this study does not allow us to ultimately address this ambiguity. However, since these studies were conducted on different platforms (Weibo and Twitter), we assume that cultural differences regarding the expression of emotions in general and on microblogging in particular can account for these apparent inconsistencies [28, 33]. As this study analyzes organizational messages on Twitter delivering both news and non-news, we generally expect a higher degree of emotionality – independent from its positive or negative form – to be beneficial for building relational outcomes.

As for the communicative approaches, based on the message content research differentiates between a more bidirectional conversational approach and an information redistributing disseminative approach

[19]. Direct user mentionings (or "@-mentionings") encompass messages that intend to strike up a conversation with the recipient, are intentional replies to a previous tweet or – in case of an ongoing conversation – are both [19]. In any case, these tweets are specifically targeted towards one or more users explicitly mentioned in the text in order to gain the target persons' attention, which is essential for conversations to occur [41]. Thus, from a communication pattern point of view, the frequent use of @-mentionings represents a conversational approach which demonstrates a company's appreciation of the individual user [19, 59]. In distinction from the common @-mentionings, companies can chose to share information from other sources through retweeting. While this structurally also implies the use of an @-symbol, its meaning is essentially different [15]. The predominant use of retweets is characteristic for a disseminative communication approach [19]. Other research has shown that retweets are commonly associated with a larger amount of hashtags and URLs compared with directed @-messages. This opposing relation is presumed to be compelled by the content feature trade-off due to the limited tweet length [98].

Thus, in our research approach we differentiate between the more personalized conversational communicative approach as opposed to the information redistribution oriented disseminative approach. Although we assume the disseminative approach to be associated with a larger amount of information in terms of URLs and hashtags, the originality and uniqueness of the information provided through these tweets is low compared to the conversational approach [19]. Moreover, it is important to remember that the latter approach does not mean to omit hashtags or URLs at all but to reduce the number of supplementary information to address users specifically. Although, no research has yet explicitly investigated the relation between content approach and sentiment, we expect the conversational approach to be more emotional due to the more personal character of the interactions. From a relationship marketing perspective, potentially relationship building message characteristics include the recognition and use of a customer's name as well as a personal and transparent interaction with the user [6, 108]. Considering the greater expression of appreciation for the individual, the bigger effort expended in generating original tweets, and the emotionally closer interaction, we assume that a conversational approach corresponds with a larger amount of relationship investment compared with the disseminative approach [79]. Thus, regarding the content features we hypothesize:

Hypothesis$_3$: A higher relationship investment in form of a conversational communicative approach leads to improved relational outcomes in terms of word of mouth and attitudinal loyalty.

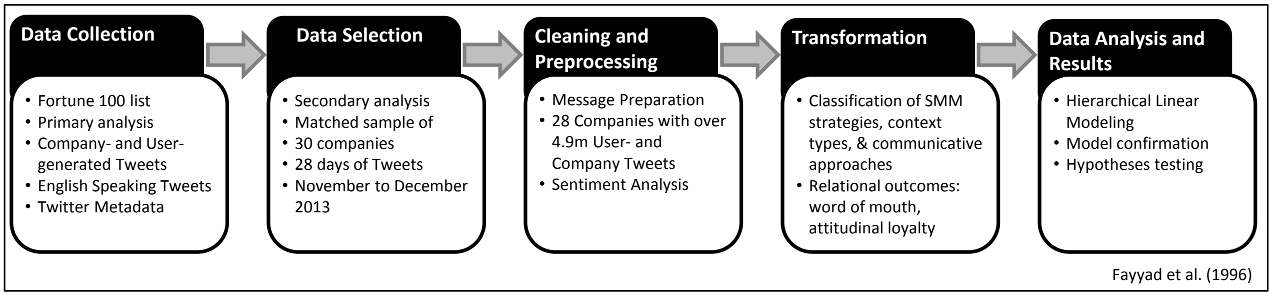
In the following, we further elaborate on the details of the empirical study we conducted to test these hypotheses.

Empirical Study

The general goal of relationship marketing is to build loyal customers who advocate a company and its products. Social media activity has proved to be a viable solution for influencing relational outcomes. However, research still lacks profound understanding regarding the impact of different social media management strategies, the manageable account characteristics, and the content related communicative approaches which enable building relational users. Thus, we identify and analyze communication and context characteristics as well as social media management strategies on Twitter regarding their corresponding effects on relational outcomes.

Data Collection, Selection, and Preprocessing

We conducted a social media analysis to address our research question of how companies' relationship marketing investment influences their relational outcomes among users on social media. Specifically, we collected and analyzed tweets from companies and users to determine the effect of different social media activities on the word of mouth and attitudinal loyalty of users. Hereby, we introduce and follow the knowledge discovery process for big data analytics described by Fayyad, Piatetsky-Shapiro and Smyth [30] as figure 3 illustrates. Since handling social media data poses considerable challenges regarding, e.g., the large volume, temporal dynamics, degree of data structuredness, or interpretament of measures, a deliberate analytical approach seems essential [2, 97]. For our research approach we decided to orient towards the established model proposed by Fayyad, Piatetsky-Shapiro and Smyth [30] since it is more comprehensive and elaborate across all analytical steps compared to other models [96]. Hereafter, we will describe the entire research process in further detail in reference to the different stages.



Figure$_3$. Stepwise approach for analyzing the efficacy of different social media activities to improve relational outcomes

In the first step of our research approach, we *collected the data to* analyze the strategic impact of applying social media management tools. The data for our research was taken from the microblogging platform Twitter that allows users to share messages containing up to 140 characters. In terms of language, we focused on all tweets written in English. As an initial sample we selected large global companies based on the Fortune 100 list [32] with varying industry sectors, such as the financial services industry, consumer brands, car manufactures, and IT companies. The data collection from Twitter was done using two separate systems at two succeeding time periods (primary and secondary analysis period). During the primary analysis period, one system was used to identify the social media management strategy while in the secondary analysis period, the second system was applied to measure the content, context and outcome variables (see second step). The first system gathered tweets sent from the primary corporate Twitter accounts through the Twitter Search API over a period of seven months. Since the Search API was restricted to 180 queries per 15 minutes, 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, products or countries). The overall database of Twitter messages comprises approximately 250,000 company-generated tweets. The metadata of these tweets revealed over 100 different sources [sometimes also referred to as 'clients'; 19] which were classified in terms of the aforementioned SMMT, Web, Mobile or any Add-On approaches.

In the second step of *data selection*, several criteria were applied to determine the company sample for the subsequent preprocessing. Several companies were dropped from further analysis as they did not have an officially verified Twitter account (i.e., Apple or several Chinese companies) or because they were inactive during our entire data gathering period. Moreover, for each company we screened tweets to test if they can be assigned meaningfully. Companies with overly ambiguous names (i.e. Google, UPS, or HP) were removed from the data set since these companies cause considerable data noise. The remaining company accounts were classified based on the predominant social media management strategy into professional SMMT and Web-based tweeting, as we will elaborate on in more detail below. We controlled for potentially perturbing effects of different a-priori publicity by matching the remaining companies in descending order, based on the number of user-generated messages containing the company name. Consequently, based on the highest number of user tweets we selected 15 SMMT and Web accounts each. For these remaining 30 accounts, we applied the second data collection system of a professional social media management provider during the secondary analysis period. Over a 28 days period from November 12th till December 10th, 2013 we had access to data from a professional social media management provider appropriating 100% of the company- and user-generated messages that explicitly mention a company name, a company's Twitter account, the platform generic company notation (keyword sample) or include a link directing towards a webpage that contains the company's name (e.g. online retailers or news sites). Thereby, we avoid the shortcomings of the common data collection approach of tracking hashtagged tweets and can obtain more in-depth measures [20]. This data sample was further preprocessed in the next step and afterwards transformed to obtain content, context and outcome measures.

The third step comprises the *cleaning and preprocessing* of the Twitter data for the subsequent regression analysis. Initially, we divided our sample in company and user-generated tweets. Due to the missing company tweets in an erroneous data export we had to exclude one web-based company and the corresponding SMMT match. For the company tweets we only considered tweets from the aforementioned main account. Furthermore, we manually screened the user tweets for usernames, which were erroneously collected because they included one of the search-keywords but did not contain information about the companies themselves (e.g., Xerox_MyFresh). Likewise, we removed tweets directed towards or sent from accounts of events (i.e. golf tournament) or locations (i.e. stadium) that were sponsored by the companies. Although we acknowledge that these sponsoring activities are of certain relevance for the companies' general public perception, considering our relatively short period of data collection these events overly distort the general representativeness of the data. The final dataset used to measure the mediating and outcome variables comprises 4,924,688 user-generated and 28,108 company-generated tweets. Subsequently, we assessed the sentiment of every single user and company tweet with an automated unsupervised sentiment analysis to obtain reliable and valid measures for our research context [56, 65]. For this purpose we deployed the publicly available tool "SentiStrength 2" developed by Thelwall, Buckley and Paltoglou [99]. From the various available sentiment analysis tools, we decided to use SentiStrength because it is especially designed to analyze the sentiment of short informal texts (i.e. microblogs) and has proven to be the most elaborate approach compared with other word lists (i.e. ANEW) [75]. Moreover, the underlying algorithm accounts for a variety of grammatically wrong but in social media often used forms of writing. In general, the sentiment analysis process comprises two consecutive steps: determining the presence of a subjective statement and classification of the sentiment value [64]. Specifically, the sentiment algorithm follows a dictionary approach to analyze messages based on a list of predefined words which signal subjectivity [64, 106]. This word list is based on the General Inquirer dictionary adjusted with human polarity coding and strength judgments [99]. The entire dictionary comprises more than 2,500 words and radicals which signal emotions in text, including also lists for negating words, question words, emoticons, and words enhancing the sentiment strengths of other words (e.g., very, little). As result, the SentiStrength algorithm computes a sentiment assessment between -5 to +5 for every message depending on the polarity of the message. In our analysis we differentiate between positive, neutral, negative, and ambivalent messages. The latter refers to messages that contain a positive and a negative sentiment, however, their polarity adds up to zero. The remaining steps of data transformation and analysis are described in the following sections.

Transformation

In the following step, we transformed our dataset into the different predictor variables (social media management strategy, context type, and content features) and dependent variables (word of mouth and attitudinal loyalty) to represent the data comprehensively regarding our research question.

Social Media Management Strategy. We differentiate between social media management strategies based on the predominant Twitter engagement approach, which a company adopts to interact on Twitter. To identify which strategy a company pursues we analyzed the company tweets collected during the preliminary data collection phase. Thus, we counted the company specific number of tweets from Web, SMMT, Add-Ons or Mobile. Hereby, the company specific distribution of engagement approaches differentiates the social media management strategies. According to our assumptions, the primary engagement approaches of Web and SMMT determined the general strategy differences. Companies predominantly engaging via SMMT or Web on Twitter (sending more than 60% of tweets from either one) were classified accordingly (see table 1). We also empirically analyzed the engagement differences between strategies. Therefore, we first conducted a MANOVA which revealed significant differences between groups concerning the engagement approaches ($F_{8,19}$=86.263, p<.01,ηp^2=0.973). As table 1 illustrates, a-posteriori ANOVAs confirmed our assumption that the strategies predominantly differ in the primary engagement approaches (Web: $F_{1,26}$=281.352***, p< 0.01; SMMT: $F_{1,26}$=325.536***, p< 0.01) and not in the secondary ones (Add-on: $F_{1,26}$=0.815$_{n.s.}$, p> 0.1; Mobile: $F_{1,26}$=1.549$_{n.s.}$, p> 0.1). For the following HLM regression analysis we dummy coded the social media management strategy with the Web strategy as a reference group so that the regression weight indicates the expected surpassing effect of the social media management strategy compared with Web [23].

Social Media Engagement Approaches	Social Media Management Strategy		Test Statistic	p-value
	Web	SMMT		
Absolute Frequency[#]				
Twitter Web-Frontend Client (Web)	889.21 (804.85)	255.57 (497.46)	$F_{1,26}=6.279$	$< 0.05^{*}$
Social Media Management Tool (SMMT)	118.93 (330.38)	1802.07 (1212.15)	$F_{1,26}=25.127$	$< 0.01^{***}$
Add-On Social Media Tool (Add-On)	36.5 (44.67)	32.86 (44.84)	$F_{1,26}=0.046$	$> 0.1_{n.s.}$
Mobile Device Application (Mobile)	40.36 (44.18)	34.21 (60.42)	$F_{1,26}=0.094$	$> 0.1_{n.s.}$
Relative Frequency[%]				
Twitter Web-Frontend Client (Web)	83.95 (13.16)	8.62 (10.37)	$F_{1,26}=281.352$	$< 0.01^{***}$
Social Media Management Tool (SMMT)	4.27 (8.44)	85.03 (14.46)	$F_{1,26}=325.536$	$< 0.01^{***}$
Add-On Social Media Tool (Add-On)	7.33 (10.67)	4.08 (8.23)	$F_{1,26}=0.815$	$> 0.1_{n.s.}$
Mobile Device Application (Mobile)	4.45 (4.17)	2.26 (4.22)	$F_{1,26}=1.549$	$> 0.1_{n.s.}$

Notes. Company sample size = 28; standard deviations are in parentheses below group mean
p-values. *** p < 0.01; ** p < 0.05; * p < 0.1; n.s.= non-significant (two-tailed significance)

Table$_1$: Results from a-posteriori groupwise comparison between social media management strategies regarding social media engagement approaches

Context characteristics. Based on social media analytics literature from diffusion network analysis, we consider different tweet metrics which we empirically aggregate into context types to capture different account types in the dataset and analyze their effect on a company's relational outcomes on Twitter [19]. Context characteristics relate to immediately manageable features of the company's Twitter account [66, 98]. Thus, for each company account we measured its status by counting the total number of messages that it had sent since its beginning. Moreover, we considered whether the company officially verified its account on Twitter as a measure for its trustworthiness. Finally, the number of friends represents the number of accounts which a company itself decides to follow [66]. In reference to Suh, Hong, Pirolli and Chi [98], we propose the differentiation between broadcasting and receiving account types dependent on these context characteristics.

Thus, we conducted a confirmatory cluster analysis to derive the respective context types. Cluster analysis allowed us to identify groupings of context types where variance in the engagement approaches is minimal within the group but maximal across groups [51]. This process involved deriving distinct and meaningful clusters from the application of the three context characteristics. We followed the two-step process recommended by Ketchen and Shook [52], and Merchant [70] to identify the general types. First, we conducted Ward's hierarchical clustering method and inspected the squared Euclidean distances trend across the clusters in the dendrogram. The results of this procedure confirmed the assumed two-cluster solution. Second, we evaluated the robustness of this solution by generating one-, three-, and four-cluster solutions with the *K*-means clustering algorithm. All of these alternative solutions either produced less meaningful clusters or had a weaker discriminatory power. Furthermore, we replicated the two-stage clustering procedure with several randomly selected sub-samples and different clustering algorithms. Each time the same two-cluster pattern was induced, providing support for the stability of this solution.

We therefore concluded that the two-cluster solution best captured the account context types in this sample.

Considering the clusters' context characteristic patterns, we labeled the first cluster "Receiver" (N = 17) and the second "Broadcaster" (N = 11). Table 2 depicts the mean average proportion of the context characteristics for each company of the respective context type as well as inferential statistics for the group comparisons. To test for differences between the context types in the context characteristics, post-hoc analysis with ANOVAs showed significant differences in Status ($F_{1,26}=4.228^{**}$, $p<0.05$) and Friends ($F_{1,26}=3.918^{*}$, $p<0.1$). Moreover, the Pearson chi-squared test revealed tendentially significant differences between context types in the account verification ($\chi^2=3.02^{*}$, $p<0.1$). Thus, we find that broadcaster generally verify their accounts more often, follow more users, and send more messages than the predominant receiver company accounts. For the succeeding HLM regression analysis we dummy coded the context types with the receiver as a reference group so that the regression weight shows the surpassing effect of the broadcaster type compared with receiver [23].

Account Type	Group Size	Context Characteristics		
		Verification	Status	Friends
Receiver	17	76.47 (43.72)	3,836.99 (3,211.74)	2,341.12 (4,592.49)
Broadcaster	11	1.00 (0.00)	67,203.49 (128,348.45)	28,485.63 (54,735.6)
Test Statistic		$\chi^2=3.02^{*}$, $p < 0.1$	$F_{1,26}=4.228^{**}$, $p < 0.05$	$F_{1,26}=3.918^{*}$, $p< 0.1$

Notes. Company sample size = 28; standard deviations are in parentheses below group mean
Tests. Verification: Pearson chi-squared; Status and Friends: univariate ANOVA

Table2: Results from a-posteriori groupwise comparison between context types regarding context characteristics

Content Features. Drawing on social media analytics literature from content analysis, we consider different textual metrics which we empirically aggregate into a content factor to capture and analyze communicative patterns in the dataset [19]. In line with prior social media analytics literature, we approximate the amount and quality of information within each message by counting the individual number of Hashtags and URLs [66, 98]. Additionally, we considered the tweets' objectivity in terms of the absence of an emotional sentiment [66]. Regarding the emotionality, in accordance with recent findings T-Test revealed that if companies entail sentiment in their tweets it is rather positive than negative ($\bar{x}_{pos}=39.45$, $\bar{x}_{neg}=9.21$, $T=9.791$, $p<0.001$) [8]. Finally, we assessed the communicative approach as elaborated above through the amount of directed @-mentionings (proxy for a conversational approach) and registered whether the tweet was a retweet (proxy for a disseminative approach) by applying the regular expression method of scanning for typical retweet text markers [15, 98]. Subsequently, we conducted confirmatory principal component factor analyses of the content features to empirically aggregate one overall content factor with specific factor scores per company per day (see table 3) [23]. Therewith, we also sample-centered the microregressor which is necessary in HLM to obtain clearly interpretable regressors [85]. The factor analysis was based on 606 observations since 178 days were missing values whenever a company sent no tweet that day (typically during the weekends) with one factor explaining 41.26% item variance. The factor loadings were in line with our assumptions based on prior findings indicating the trade-off between communication approaches [98]. Specifically, on the one side we find negative loadings for hashtags, URLs, objectivity, and retweets while on the other side a positive loading of @-mentionings. Thus, the regressor can be interpreted in the way that a positive relation between the content factor and the relational outcomes indicates the impact of the conversational approach on building relational outcomes while a negative relation shows the impact of the disseminative approach.

Item specific statistics	Content Features				
	Hashtag	URL	Objectivity	Retweet	@-Mentioning
Relative Frequency	49.72 (35.52)	65.28 (35.6)	47.87 (30.84)	22.97 (31.95)	71.43 (32.97)
Factor Loading	-0.673	-0.873	-0.638	-0.38	0.545
Extracted Commonality	0.453	0.762	0.407	0.145	0.297
Notes. Day specific sample size = 606; standard deviations are in parentheses below group mean					

Table$_3$: Results from principal component factor analysis of message content features

Relational Outcome Variables. To analyze the effect of social media relationship investment on relational outcomes we consider different customer focused outcome variables which have been identified as relevant measures for the success of relationship marketing (see table 4). This study, however, incorporates partly unique operationalization which have not even been considered in other studies so far. First, we consider word of mouth which comprises the two key attributes of valence and volume [21] which have been previously considered in the microblogging environment [44]. To estimate the valence we computed the average daily sentiment of all user tweets based on the scale from negative to plus five separately for each company. Considering the importance of emotional messages in general to build brand awareness, we consider the undifferentiated share of emotionality among the user messages [94]. Thereby, we appropriate emotionality through its complement share of neutral messages with a larger share of neutral messages indicating less emotionality. Additionally, we considered the companies' share of voice through the number of user tweets containing the company name as a proxy for the volume characteristic of word of mouth. Second, attitudinal loyalty is defined as a user's affinity towards a company. Thus, we used the daily number of followers as a measure for relationship quality since it indicates how strongly a company is connected with the users who voluntarily demonstrate their affinity towards the company [22]. Moreover, we counted how often on average company tweets were retweeted and tagged as favorites by users. Although both measures are somewhat related in the sense that both indicate a strong user involvement with the companies, it is our understanding that both measures differ regarding the target of expression. While, on the one hand, user retweeting can serve different hidden intentions, it generally demonstrates the interest in and connectedness with the retweeted content to the own followers within one's network [15]. Thus, retweeting messages demonstrates a better connection with the source of the information to others. It needs to be noted that this outcome measure of retweets refers to how often a company tweet has been redistributed by users and is not to be confounded with the aforementioned content retweet feature which describes how regularly a company simply disseminates others' content instead of providing original information. Favorites, on the other hand, serve as a positive feedback for the company that a user agrees with or likes a certain statement. We understand Twitter-Favorites to be comparable to Facebook-Likes (which have been investigated more thoroughly) in the sense that they are used as a mechanism to express a positive association with online content [53]. Thus, favoring messages indicates similarity of interests and demonstrates a closer relation to the company. While the practice of retweeting has received a certain amount of attention, favorites are generally less commonly given and have thus have been understudied by extant research [e.g., 15, 66, 98].

Social Media Activities	**Word of Mouth**			**Attitudinal Loyalty**		
	Average Word of Mouth	Share of Voice	Neutrality	Follower	Retweets	Favorites
Web	0.11 (0.09)	3,230.07 (5,583.19)	55.63 (11.17)	72,169.45 (96,627.82)	11.44 (13.72)	12.43 (19.32)
SMMT	0.13 (0.08)	9,332.91 (8,810.14)	56.41 (9.72)	507,497.53 (719,687.11)	55.19 (114.42)	30.78 (54.37)
Receiver	0.09 (0.08)	4,764.2 (8,506.62)	59.29 (10.86)	181,304.82 (415,230.24)	45.46 (105.26)	27.06 (51.66)
Broadcaster	0.16 (0.07)	8,626.4 (6,461.93)	50.97 (7.13)	457,559.61 (700,924.6)	14.53 (15.41)	13.16 (12.85)
Communicative Approach	0.303	0.138	-0.328	0.043	-0.108	-0.125

Notes. Standard deviations are in parentheses below group mean; Pearson Correlation coefficients depicted for the communicative approach factor

Table$_4$: Overview of descriptive statistics for social media management activities regarding relational outcome variables

Analysis and Results

We applied hierarchical linear modeling (HLM) since it empirically reflects the multilevel structure of our approach [55, 85]. Thereby, HLM is robust against unbalanced data and processes cross-level interdependent observations. By segregating the individual variance of the dependent variable into multiple levels, HLM allows for a distinct interpretation of potentially confounded regressors due to level interdependencies. Moreover, this approach has advantage over standard regression approaches since it controls for level specific unobserved heterogeneity by including additional random- or fixed-effect terms as proxies for unobserved individual characteristics [107].

Focusing on the dayspecific relational outcomes as our unit of analysis, we estimated our theoretical model and the hypothesized effects based on three nested models that reflect the underlying hierarchical structure of relationship marketing on social media (see tables 5 and 6). By estimating three different models we seek empirical evidence for the multi-level structure of our research approach and analyze the specific impact of interaction level based message features or the broader company account characteristics of context type and social media management strategy. Thus, for each outcome variable we stepwise-complemented a simple baseline model (Model 1) with the specific regressors elaborated in the theoretical development and transformation section (i.e., content, context, strategy) to consider changes in the model fit [85]. Accordingly, the unconditional baseline *Model 1* included only the random intercepts. Next, we obtained *Model 2* by adding the dayspecific content factor scores to test our hypothesis$_3$ on the microlovel (Level-0). In *Model 3*, we amended the macrolevel company specific dummy regressors of context type and social media management strategy to investigate our respective hypotheses 1 and 2 (Level-1).

We conducted a random intercepts mixed-effects maximum likelihood regression procedure to estimate the regression parameters and calculate the corresponding Satterthwaite-corrected t-statistics and p-values for the path coefficients [42]. While acknowledging the complex discussion of required sample sizes for HLM analysis, we consider the sample of 28 daily data points for each of the 28 companies to approximate the recommended mimimum number considering our main research focus on fixed effects [42]. Moreover, we evaluated the different models by comparing their goodness-of-fit test statistics [69]. Specifically, we computed the established restricted maximum log-likelihood values, Akaike's information criterion (AIC) [13], and the Bayesian information criterion (BIC) [90]. Furthermore, we analyzed the appropriateness of the multilevel structure by comparing the mixed models with the standard regression models without cross-classified random effects in their likelihood ratio [42]. For all models and outcome variables the results show a highly significant increase in fit ($p < 0.01$) for the mixed models compared to the standard OLS regression models. Moreover, considering the variance based character of the goodness-of-fit measures, the generally significantly decreasing values confirm the validity of our proposed models (Model 2 and Model 3) regarding validity and complexity in comparison to the baseline (Model 1). This, however, does not hold true for the neutrality analyses, where no significant model-fit improvement was attained.

DV / IV	Average Word of Mouth			Share of Voice			Neutrality		
	$Model_1$	$Model_2$	$Model_3$	$Model_1$	$Model_2$	$Model_3$	$Model_1$	$Model_2$	$Model_3$
Level-0									
Intercept	0.094*** (0.014)	0.103*** (0.013)	0.083*** (0.019)	6.281*** (1.488)	6.452*** (1.509	3.404** (2.113)	0.560*** (0.019)	0.561*** (0.017)	0.572*** (0.025)
Content		0.007 (0.008)	0.003 (0.008)		0.378** (0.172)	0.372** (0.172)		-0.016*** (0.006)	-0.014** (0.006)
Level-1									
Context			0.055* (0.032)			0.691 (3.369)			-0.067* (0.04)
Strategy			0.002 (0.028)			5.641* (3.144)			0.023 (0.037)
Intercept Variance									
Level-0	0.164	0.137	0.136	0.026	0.026	0.026	0.113	0.096	0.096
Level-1	0.068	0.062	0.061	0.079	0.08	0.077	0.1	0.089	0.088
Log-Likelihood	224	275	272	-7,448	-5,751	-5,731	490	469	465
χ^2 (model improvement[1])		104***	-6.83		3,394***	40***		-42	-7
AIC	-440	-542	-531	14,904	11,512	11,476	-972	-928	-917
BIC	-421	-520	-500	14,923	11,534	11,507	-953	-906	-906
$N_{company}$	28	28	28	28	28	28	28	28	28
N_{day}	778	605	605	784	606	606	778	605	605

Notes. Company sample size (Level-1) = 28, day specific sample size (Level-0) = 606; standard errors are in parentheses below unstandardized coefficients; share of voice figures depicted in thousands; DV = dependent variable; IV = independent variable
p-values. *** p < 0.01; ** p < 0.05; * p < 0.1 (two-tailed significance)
[1] Likelihood ratio test statistic: -2ln(likelihood null model) + 2ln(likelihood alternative model)

Table$_5$: Results of the hierarchical linear modeling estimations regarding word of mouth

To test hypothesis$_3$, we included the microlevel content factor scores with positive loadings indicating the effectiveness of an increasingly conversational approach to build relational outcomes. Regarding the word of mouth, in accordance with our hypothesis, we find a stable significant negative relation between the content factor and neutrality (Content = -0.014**, $p < 0.05$). Thus, the less conversational the company communication is on Twitter, the higher the neutrality of user messages. In other words, an increase in conversational communication translates into an increase of emotionality among user word of mouth and thus supports brand awareness. Concurrently, a more conversational communication from the company is also associated with a larger share of voice among the users (Content = 0.372**, $p < 0.05$). Furthermore, contrary to our hypothesis, we find a significant negative relation between the content factor and favorites (Content = -0.101*, $p < 0.1$). This indicates that users rather express appreciation for messages containing larger amounts of information than for personalized interaction. It seems likely that this effect is related to the account types under investigation. In our sample we focus on the main company accounts users primarily follow to receive information on the respective brand while they would probably show greater appreciation for personal interaction on customer service and support accounts [59]. To test this assumption, however, we will have to analyze a more comprehensive set of company accounts.

DV / IV	Follower			Retweets			Favorites		
	$Model_1$	$Model_2$	$Model_3$	$Model_1$	$Model_2$	$Model_3$	$Model_1$	$Model_2$	$Model_3$
Level-0									
Intercept	289.835^{***} (104.028)	289.829^{**} (104.029)	42.509 (141.357)	0.339^{**} (0.158)	0.334^{**} (0.155)	0.181 (0.229)	0.221^{***} (0.079)	0.216^{**} (0.076)	0.139 (0.116)
Content		-0.093 (0.714)	-0.096 (0.714)		-0.104 (0.096)	-0.071 (0.101)		-0.111^{*} (0.053)	-0.101^{*} (0.057)
Level-1									
Context			207.549 (225.527)			-0.435 (0.366)			-0.106 (0.185)
Strategy			361.211^{*} (210.653)			0.578^{*} (0.33)			0.216 (0.166)
Intercept Variance									
Level-0	0.073	0.074	0.074	0.161	0.162	0.162	0.094	0.094	0.094
Level-1	0.055	0.055	0.051	0.074	0.072	0.071	0.035	0.033	0.034
Log-Likelihood	-6,663	-6,656	-6,627	-4,001	-3,997	-3,987	-3,667	-3,663	-3,654
χ^2 (model improvement[1])		15^{***}	58.28^{***}		7.52^{***}	21.08^{***}		9.42^{***}	16.67^{***}
AIC	13,333	13,320	13,266	8,010	8,005	7,988	7,343	7,335	7,323
BIC	13,346	13,337	13,292	8,028	8,027	8,019	7,361	7,358	7,354
$N_{company}$	28	28	28	28	28	28	28	28	28
N_{day}	784	606	606	784	606	606	784	606	606

Notes. Company sample size (Level-1) = 28, day specific sample size (Level-0) = 606; standard errors are in parentheses below unstandardized coefficients; follower figures depicted in thousands; DV = dependent variable; IV = independent variable
*p-values***.** *** p < 0.01; ** p < 0.05; * p < 0.1 (two-tailed significance)
[1] Likelihood ratio test statistic: -2ln(likelihood null model) + 2ln(likelihood alternative model)

$Table_6$: Results of the hierarchical linear modeling estimations regarding attitudinal loyalty

We tested $hypothesis_2$ by including the dummy-coded context variable with positive coefficients indicating increased effectiveness of the broadcaster account type compared with the receiver. Supporting our hypothesis, we find a positive impact of the broadcaster on the word of mouth. Specifically, the results confirm a significantly more positive word of mouth valence for the broadcaster type compared with the receiver (Context = 0.055^{*}, $p < 0.1$). Even though the overall model fit deteriorates between model 2 and model 3 due to the increased complexity of estimating more path coefficients, model three still has significantly higher validity than the baseline-model (model 1). Moreover, in addition to the aforementioned positive effect of the content factor, broadcasting also significantly decreases the neutrality share within the user messages (Context = -0.067^{*}, $p < 0.1$). Thus, we generally find that an increased relational investment in terms of a broadcasting account type not only causes more emotional user messages but also improves the user sentiment for the company. However, we do not observe any differential effects of the context types on measures for attitudinal loyalty.

$Hypothesis_1$ was tested through amending the dunmy-coded social media management strategy variable into our model with positive regression coefficients indicating incremental value of applying an SMMT compared with a simple web strategy. In line with our assumptions, we found a significant positive relation between the SMMT strategy on the word of mouth volume characteristic of user share of voice (Strategy = 5.641^{*}, $p < 0.1$). Regarding the attitudinal loyalty estimates we found beneficial effects on follower numbers (Strategy = 361.211^{*}, $p < 0.1$) and the retweet probability (Strategy = 0.578^{**}, $p < 0.1$) of the more profound SMMT strategy. It can be argued that the application of SMMTs helps to understand and address the users' interest which, in turn, causes them to follow a company more often and to even pass on the company messages to their own network. This shows that a larger relationship investment in form of a more professional social media management strategy provides companies with deeper insights into the network trends and enables a more profound engagement with the customers, which ultimately improves the public perception among the users.

Discussion

The goal of our study was to apply social media analytics tools and theory to investigate the effect of social media relationship investment on relational outcomes on Twitter. We conducted a multilevel analysis based on the data of approximately 5 million user and company tweets concerning the Twitter accounts of 28 large global companies over a 28 days period. Thereby, we distinguish the company's amount of relationship investment within different social media management strategies, manageable context characteristics, and content related communicative approaches regarding their efficacy to improve the word of mouth and build attitudinal loyalty. By considering the company-specific arrangement engagement approaches (SMMT, Web, Add-On, and Mobile), we distinguish between the simple Web-based and the more profound SMMT strategy on social media. Moreover, we draw on existent social media analytics literature to identify key company account characteristics (verification, friends, and status) which have been found to influence the public perception. Based on these characteristics we empirically derive the less active 'receiver' profile and the more engaged 'broadcaster' account type. Similarly, we assess text-based content features (hashtags, URL, sentiment, retweets, @-mentioning) and empirically aggregate them into a communicative approach factor. In reference to preliminary social media analytics research, we differentiate between impersonal disseminative communication and the customized conversational approach.

Finally, we tested the effects of these engagement activities on relational outcomes in a multilevel HLM regression. The results confirm our assumption of a multi-level social media engagement which requires empiricism to adopt appropriately in order to avoid statistical fallacies [97]. Moreover, our analysis supports the three hypotheses regarding benefitial effects of relationship investment on Twitter in form of message content, account context and social media management strategy on user word of mouth as well as attitudinal loyalty. Regarding the unexpected finding of beneficial effects for disseminative communication on attitudinal loyalty, we have reason to believe that the observed effect can be ascribed to the selection of the company's main account in this study. It seems likely that future research which considers differential effects of relationship investment in terms of different company account types would find conformably differential effects [59, 86]. Furthermore, seeing that neither outcome variable is simultaniously affected by all predictors shows the necessity for considering multiple outcome variables and delibarately choosing appropriate outcome measures in social media analytics research. Our results show that neither action on social media platforms serves as a silver bullet to build strong brand-centric communitites but that different approaches have distinct effects on relational outcomes.

Conclusion

Generally, the results commonly support our hypotheses of increased relational outcomes in terms of better word of mouth and attitudinal loyalty attained through a higher relationship investment in form of the SMMT strategy, broadcasting account type, and conversational communication. Results regarding attitudinal loyalty measures do not entirely correspond to the word of mouth pattern. Here we find a positive effect of a disseminative communicative approach on the probability of favorites. It seems likely that this observation is related to our sample of main company accounts where users primarily follow to receive information. Thus, we assume that users would probably show greater appreciation for personal interaction on customer service and support accounts [59]. Future research investigating social media management activities should analyze the role of different account forms (e.g., recruiting, sales, customer service) and the associated company business strategy [24].

Theoretical and Practical Implications

Our research offers substantial implications for both research and industry alike by addressing recent calls for effective social media management strategies [5, 82] and analyzing the importance of social media analytics for successful social media community management [97]. Regarding the theoretical contributions, the pursued social media analytics approach addressed economic questions regarding the successful management of social media, the value of social media management applications, and measures for success on social media [97]. Specifically, we provide further insights into the interdependence between different context and content variables. Thereby, we empirically identify and elaborate overall patterns of social media use in form of the different account types (receiver vs. broadcaster) and communication approaches (disseminative vs. conversational). Regarding the account typology, research had neither simultaneously considered the interdependence of verification, status and friend characteristics nor developed a conceptual counterpart (i.e. receiver) for the broadcasting type. Similarly, the concepts of conversational and disseminative conversation had been limited to the comparison of @-mentionings and retweets as well as disregarded a comprehensive assessment of all message features including the message sentiment. The work at hand extends the current research state of the art by comprehensively including the various context characteristics and content features and deriving broad behavioral patterns. With this research we are able to demonstrate the value of social media analytics for building loyal brand advocates and relational users in form of the positive SMMT strategy effects. Our results illustrate that social media analytics enabled insights into the user network are important to improve the share of voice among the users, increase follower numbers and the retweet probability. It is plausible to assume that the application of SMMTs will increase in the years to come and that this will be an area of growing interest for service providers, as the recent acquisition of a social media management provider by Twitter illustrates [93]. Thus, this work shares insights into innovative business applications and value discovery using social media analytics. Furthermore, this research extends the body of knowledge on social media analytics by introducing and asserting two alternative theoretical perspectives. First, considering the challenges of handling social media data (e.g., volume, dynamics, data structuredness) it is necessary to adopt an elaborated analytical approach [97]. In this study, the knowledge discovery process for big data analytics described by Fayyad, Piatetsky-Shapiro and Smyth [30] has proven successful in guiding us through our analytical steps and in removing data noise to extract useful signals. We thus encourage future research to follow this approach in order to ensure the reliability and validity of results. Second, we introduce relationship marketing theory to develop our hypotheses, support our research model, and found the operationalization of the measures. It seems necessary to prospectively adopt a common theoretical foundation considering that researchers previously used the same measure inconsistently for different constructs (e.g., followers for brand awareness and brand engagement) [29]. From a relationship marketing perspective these inconsistencies can be ascribed to the confusion of antecedents (e.g., word of mouth) and consequences (e.g., brand awareness) [21]. Moreover, we derive the measures of neutrality and favorites to expand the assessment of word of mouth and loyalty on social media platforms. On the one hand, the share of neutral messages about a company enables to estimate the companies' emotional appeal which is an important precursor of brand awareness. On the other hand, the number of favorites measures the individual's expression of endorsement for a brand towards the company as opposed to the declaration of appraisal within one's network through retweets. Given the results, it can be assumed that further consideration of relationship marketing literature might help to overcome current value measurement difficulties on social media [29, 47, 60]. Additionally, our results support the assumption of a multilevel structure of social media activities. Thereby, we provide empirical support for the call for more complex analyses of social data [97]. Instead of focusing on singular layers of interaction (only message or account characteristics), research should consider the complexity of nested models. Accordingly, our results show a significantly better fit of the multilevel HLM regression models compared with the standard regression models prevailing in social media analytics. Thereby, the mixed-models approach helps to control individual variance and confounding effects.

Our work also contains important practical contributions by providing guidelines for companies to engage on Twitter and measure success appropriately [97]. This study supports the claim that companies and researchers alike need to deliberately decide on the management objective they want to attain and take corresponding actions [12, 46]. Generally, the results demonstrate that novel social media analytics applications (SMMTs) as well as content and context characteristics considerably contribute to business value. Thereby, we address the common social media measurement paradoxon by showing that actions on different levels of social media engagement translate into different outcomes [60]. For example, introducing a SMMT helps to increase the public awareness of a company in terms of word of mouth volume, follower numbers and retweets while it does not seem to significantly improve the word of mouth sentiment over the Web-based strategy. A broadcasting account type is especcially successful at improving word of mouth as it receives more positive responses from the users than the receiver type. Finally, both broadcasting type and a conversational communicative approach help to improve the brand awareness of the users. This finding substantiates the assumption that emotionally loaded non-news tweets create larger brand perception than neutral ones [36, 95]. However, we also find evidence that simply following a conversational approach simultaniously decreases the probability of users favoring the company messages. To increase tweet favorites companies should follow the disseminative content approach by redistributing information from other users. Considering the implications of these opposing effects, community managers and marketers need to decide which objective is most desireable for company success, what type of activities they want to address (e.g., branding, sales, customer service and support or product development) and adapt their communication accordingly [24]. Although research has not yet quantified the monetary benefits of relational outcomes on social media, we follow the assumption that reaching a broader range of potential customers and being more prominent in the user perception will ultimately also transfer into financial return on investment [4, 29, 87]. Moreover, researchers argue that besides monetary results, platform-based outcomes in terms of customer behavior – as we measure it – are more appropriate and equally relevant to consider as measures for returns on social media investments [31, 39, 47].

Limitations and Future Research

Our findings need to be considered in the light of the study's limitations. First, the process of data collection and processing implies certain limitations. Specifically, for our analysis we only considered tweets written in English. Although the majority of messages on Twitter is written in English, this filter limits the generalizability of our findings to certain social circles [9]. We addressed this limitation in part through the consideration of all tweets in English regardless of the country of origin. Nonetheless, non-English speaking countries are probably underrepresented in the sample. Moreover, we collected tweets based on company names as keywords. Keyword samples, however, have some inherent limitations such as missing full threads of communication if they do not contain the keyword [19]. In our case, this limitation is comparatively less prominent since @replies towards the company are also included in our data because it contains the company name. Still communication threads among users about a company will be underrepresented in our sample, since they do not necessarily always include the company reference. Also, the SentiStrength tool deployed for our sentiment analysis has major deficiencies in detecting irony and sarcasm [99]. Thus, it is probable that the sentiment scores are biased towards positive values. Considering the general difficulty of avoiding these issues and the fact that these limitations probably affect all companies alike, we do not expect them to impair the internal validity of our findings but to limit the external validity of the share of voice or the average word of mouth for example.

Second, the context of our study restricts our conclusions to microblogging platforms in general or to Twitter in particular. Considering the diverging characteristics of other social media platforms like social networking sites (e.g., regarding information sharing, innovation creation, marketing), it seems necessary to investigate the effects of our study in a different context and adapt outcome measures accordingly [37, 39]. Moreover, one could argue that rather technology-affine users participate on Twitter and that this is not a representative sample for analyzing the public perception of a company. However, since research on Twitter has managed to predict elections or stock market developments [11, 103], we believe that the data can also be used to estimate the publicity of companies. Moreover, we limited our analysis to various dimensions of word of mouth and attitudinal loyalty. As pointed out above, future research should consider additional outcome variables of relationship marketing such as user satisfaction or response times.

Third, our selection of company account implies limitations for the interpretation of our results. We find tentative evidence for a bias related to considering only a company's main account, while they typically operate multiple accounts that target customized user groups and followers with differing interests [48, 86]. Accordingly, different account types might mediate the efficacy of the communicative approaches (e.g., especially beneficial effects of conversational communication for customer care and support accounts). Consequently, Li, Berens and de Maertelaere [61] find that the efficacy of increased social media activity grows with the account specificity (e.g., specific services, products or countries). Regarding the social media management strategy, while it seems likely that one company account predominantly applies one engagement approach, it does not automatically mean that the entire company follows the same. It can be assumed that if one company account applies a SMMT that this increases the probability for another account from the same company to follow suit (e.g., due to a companywide contract or the strategy alignment across divisions). Nonetheless, it is still possible for other departments to choose not to use a chargeable SMMT. Thus, future research will also need to consider and compare differences across company accounts.

By expanding the sample size research could also increase statistical power in order to simultaneously analyze the effects of the respective sub-dimensions (e.g., impact of positive vs. negative company tweet sentiment) or conduct cross-sample comparisons to investigate a potentially moderating effect of social media management strategy on the communicative approach. Moreover, future research should elaborate on additional characteristics of communicative approaches and context types (regularity of tweets, time to response towards negative comments) and investigate the role of other social media engagement approaches (Mobile, Add-Ons), which might help to compensate shortcomings of the simple Web strategy.

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Glossary

Acronym	Object	Description
SMMT	Social Media Management Tool	Provide various social media analytics features to collect, monitor, analyze, summarize, and visualize social media data and support interaction with users in real-time.
Web	Web-Frontend Client	Engage on and monitor social media platforms through the ordinary online login like the common user.
Mobile	Mobile Device Applications	Use mobile devices to interact on social media platforms independently of time and space to support a more lively social media presence.
Add-On	Add-On Social Media Tool	Offer specialized engagement and monitoring services as a niche solution in special cases.
HLM	Hierarchical Linear Model	Generalized linear model approach to simultaneously measure effects at different levels within a nested sample.