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Social Media Metrics — A Framework and Guidelines for Managing Social Media

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Abstract

Social media are becoming ubiquitous and need to be managed like all other forms of media that organizations employ to meet their goals. However, social media are fundamentally different from any traditional or other online media because of their social network structure and egalitarian nature. These differences require a distinct measurement approach as a prerequisite for proper analysis and subsequent management. To develop the right social media metrics and subsequently construct appropriate dashboards, we provide a tool kit consisting of three novel components. First, we theoretically derive and propose a holistic framework that covers the major elements of social media, drawing on theories from marketing, psychology, and sociology. We continue to support and detail these elements — namely 'motives,' 'content,' 'network structure,' and 'social roles & interactions' — with recent research studies. Second, based on our theoretical framework, the literature review, and practical experience, we suggest nine guidelines that may prove valuable for designing appropriate social media metrics and constructing a sensible social media dashboard. Third, based on the framework and the guidelines we derive managerial implications and suggest an agenda for future research.

Keywords: Social media; Key performance indicators; Dashboard; Return on investment; Learning theory; Interactionist social theory; Network theory; Attribution theory; M–O–A paradigm

Introduction

Social media are becoming an ever more important part of an organization's media mix. Accordingly, organizations are starting to manage them like traditional offline and online media (e.g., Albuquerque et al. 2012; Hartmann 2010; Zhang et al. 2012). To this end, many organizations subsume social media metrics into their marketing dashboards as a reduced collection of key performance metrics (Pauwels et al. 2008). In a first approach, managers may be tempted to apply the concepts of traditional media metrics to the measurement, analysis, and management of social media.

However, social media are substantially different from the other media (e.g., Godes et al. 2005; Hoffman and Fodor 2010; Hoffman and Novak 2012). In contrast to other media, they rather resemble dynamic, interconnected, egalitarian and interactive organisms beyond the control of any organization. Thus, they require a distinct approach to measurement, analysis, and subsequently management.

- But what are these fundamental differences of social media?
- What are the primary interacting elements that produce outcomes with social media?
- How should organizations and researchers capture them in metrics for their analysis?
- How should organizations integrate such metrics into their social media dashboards?

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To guide organizations and researchers in developing the right social media metrics for their dashboard, we provide a tool kit consisting of three novel components. First, we theoretically derive and propose a holistic framework that covers the major elements of social media, drawing on theories from sociology, marketing, and psychology. We support and detail these elements — namely 'motives,' 'content,' 'network structure,' and 'social roles & interactions' — with findings from recent research studies. Second, based on our theoretical framework, the literature review, and practical experience, we derive nine guidelines that may prove valuable for designing appropriate social media metrics and subsequently constructing sensible dashboards. Third, based on the framework and the guidelines we derive managerial implications such as the need for more theoretically driven social media metrics in dashboards, the need for new types of marketing input for social media, and profound organizational changes that may be implied when setting up social media interfaces with various functions in firms. We suggest a corresponding agenda for future research. The following sections reflect the order of our contributions.

The Framework: Theoretical Foundation

For the derivation of guidelines on how to design appropriate metrics and subsequently construct a sensible dashboard for social media we require a proper framework. We develop this framework by first defining what constitutes a social medium, a metric, and a dashboard. In a second step, we derive a holistic framework from theoretical considerations and support it with references from recent literature on social media.

Definitions

Social Media

The term 'Social Media' is a construct from two areas of research, communication science and sociology. A medium, in the context of communication, is simply a means for storing or delivering information or data. In the realm of sociology, and in particular social (network) theory and analysis, social networks are social structures made up of a set of social actors (i.e., individuals, groups or organizations) with a complex set of dyadic ties among them (Wasserman and Faust 1994, pp 1–27). Combined, *social media are communication systems that allow their social actors to communicate along dyadic ties*. As a consequence, and in stark contrast to traditional and other online media, social media are egalitarian in nature. This means, for example, that a brand is essentially a node, or an actor, just like any other in a network. Thus, it is no longer an authority in a hierarchical '1:n'-structure that can impose an exposure to commercial messages as in other media, e.g., by buying time for commercials and 'enforcing' watching them. Of course, we see attempts to use banners or "sponsored stories" in such networks that mimic classic display advertising. But those messages are often diametrically opposed to the dialogic nature of social networks built on individual relationships, as they often rudely interfere with users' (frequently intimate) conversations with messages about (frequently unrelated) issues.

Across social media, Alba et al. (1997) describe this dyadic relational interactivity as the main differentiating characteristic of social media compared to other traditional offline and online media: a social medium is, by definition, multi-way, immediate, and contingent. Stewart and Pavlou (2002) add that social

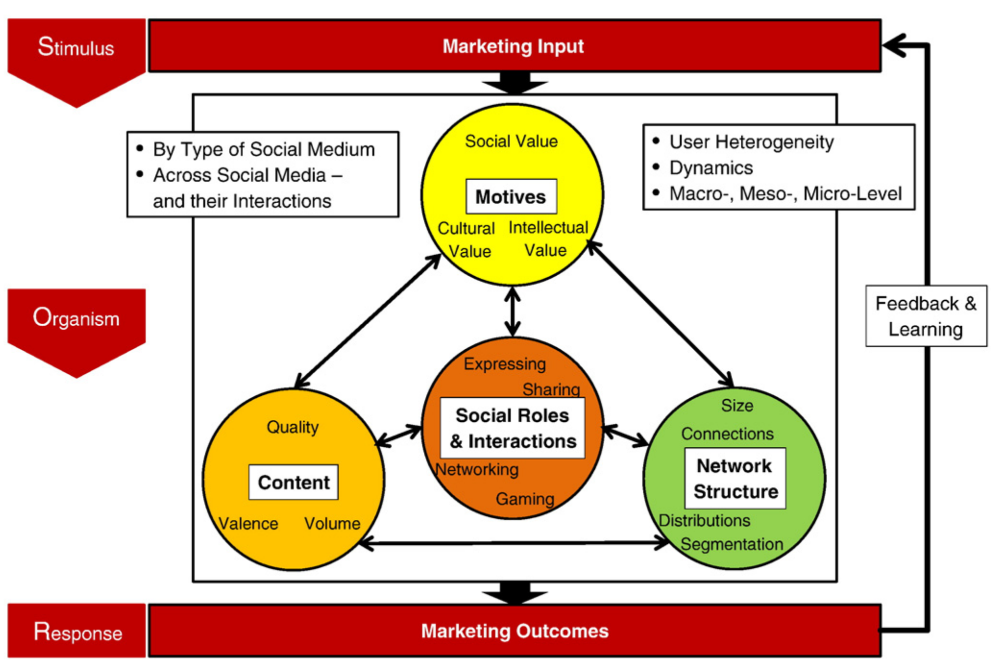


Fig. 1. S–O–R framework for social media metrics.

media may have different degrees of interactivity, and that for understanding them one must know their contingency, context and structure, goals, sequences of actions and reactions, and the characteristics of the respective medium. A plethora of social media have emerged in the last several years, and Kaplan and Haenlein (2010) describe them as a group of Internet-based applications allowing the creation and exchange of User Generated Content (UGC). Via social presence and self-presentation, they assign social media into six different groups: (1) collective projects (e.g., Wikipedia), (2) blogs and microblogs (e.g., Twitter), (3) content communities (e.g., YouTube), (4) social networks (e.g., Facebook, MySpace, LinkedIn), (5) massively multi-player online role-playing games, so-called MMORPGs (e.g., World of Warcraft), and (6) social virtual worlds (e.g., SecondLife). Taken together, these definitions already suggest that social media may require distinct metrics compared to traditional media, capturing in particular

- their network characteristics, i.e., actors and dyadic ties,
- the dynamics that reflect their immediate and multi-way nature,
- the contingency aspects of information exchanged, and
- the specifics of the respective social medium (or application).

This distinct nature of social media prohibits the simple transfer of metrics from traditional media. In order to enable the development of appropriate metrics for social media, we next revisit the criteria that constitute a metric.

Metric

Farris et al. (2006) define a metric as a measurement system that quantifies static or dynamic characteristics. More generally, one could argue that metrics either describe or quantify a state, i.e., characteristic, or a process, i.e., a dynamic, trend, or evolution. Additionally, states or processes may be stochastic and thus require additional information on the level of certainty, i.e., likelihood or variance. In research as well as business, metrics are employed to define goals, measure the degree of completion or the deviation, and subsequently implement measures to improve these metrics (Farris et al. 2006).

In a MSI workshop on brand equity metrics, Ailawadi, Lehmann, and Neslin (2003) summarize ten requirements for a metric that we evaluate with respect to the distinct characteristics of social media derived above. Accordingly, like any other metric, social media metrics require theoretical grounding, completeness, and a diagnostic nature; they also need to be credible to management and reliable over time. But due to the distinct nature of social media, we argue that objectivity may be replaced by inter-subjectivity and pragmatic corridors of comfort (see guideline #8). We also emphasize that convenience of available data or metrics should not preclude the construction of theoretically sound and important metrics (see guideline #9). In contrast to measurement in classic media, we also suggest the need for balancing metrics to sufficiently describe dynamic phenomena in social media (see guideline #6). Hence, we agree with Ambler and Roberts (2006) that pursuing a single silver-bullet metric in this context is ill-advised. We later illustrate these challenges with examples. With respect to credibility and management importance, social media metrics need to be connected to marketing actions and related to financial consequences, i.e., relevant outcomes (see De Haan, Wiesel, and Pauwels 2013; Sonnier, McAlister, and Rutz 2011 as well as Wang, Yu, and Wei 2012 for demonstrations). But as no metric alone sufficiently captures the important and diverse phenomena in social media, managers need a systematic approach to identifying and constructing the appropriate metrics. This can be done with the help of a social media dashboard which we define next.

Dashboard

Guiding managers toward the completion of their goals usually requires a sensible collection of metrics. Pauwels et al. (2008) define a dashboard as "a relatively small collection of interconnected key performance metrics and underlying performance drivers that reflects both short- and long-term interests to be viewed in common throughout the organization." An effective dashboard reflects a shared definition and understanding of key drivers and outcomes within the firm, diagnoses poor or excellent performance, allows for evaluating actions on financial outcomes, enables organizational learning, and supports decision-making to improve performance (e.g., Ambler 2003; Pauwels et al. 2008; Reibstein and Srivastava 2005).

However, the recent fragmentation of (social) media, the proliferation of additional sales channels, and the advent of "big data" manifested in the collection of UGC on the web and in social media present considerable challenges to the design of appropriate dashboards. Accordingly, Fader and Winer (2012) recommend a rather cautious approach to rich UGC data: it requires processing vast amounts of data, most of which is qualitative in nature and prohibitively time consuming to analyze. Single new metrics from social media such as likes, followers, and views might be simple, comparable to traditional media, and therefore tempting to focus on. But as much as they compare to other existing metrics on classic media in corporate dashboards, such metrics may not reflect the important aspects of social media. To the contrary, using such simple metrics in dashboards can mislead marketing efforts in a way that may even harm an organization's prospects. To arrive at appropriate metrics for a firm's (social media) dashboard, we first require a theoretical foundation and subsequent exploration of the relationship between input, metric, and financial outcomes. Accordingly, we next derive a theoretical framework for understanding social media. This serves as a foundation to enable the derivation of appropriate metrics and subsequently adequate dashboards.

A Theoretical Framework for Understanding Social Media

Overarching Framework

From a management perspective, 'understanding' social media is a prerequisite for properly managing these channels. Hence, managers and researchers need to comprehend how marketing input interacts with social media to produce desired marketing outcomes. This logic relates to the Stimulus (S) → Organism (O) → Response (R) paradigm with its feedback loop from Social Learning Theory (e.g., Bandura

Table 1
Social media content metrics in selected recent publications.

Source	Framework element	Domain	Social medium	Data	Metric	Definition (if necessary)	Type of metric
De Vries, Gensler, and Leeflang (2012)	Content	Quality	Facebook	Brand pages	Vividness	Low (pic) medium (event) high (video)	Index
De Vries, Gensler, and Leeflang (2012)	Content	Quality	Facebook	Brand pages	Interactivity	Low (link) medium (contest) high (question)	Construct
De Vries, Gensler, and Leeflang (2012)	Content	Quality	Facebook	Brand pages	Informational content	No yes	Binary
De Vries, Gensler, and Leeflang (2012)	Content	Quality	Facebook	Brand pages	Entertaining content	No yes	Binary
Chintagunta, Gopinath, and Venkataraman (2010)	Content	Valence	Review site	Yahoo! movie website	Valence	Mean rating of reviews	Rating
Godes and Silva (2012)	Content	Valence	Review site	Book reviews	Average rating over time	Average Rating	Rating
Sridhar and Srinivasan (2012)	Content	Valence	Platform	Travel website	Rating	Rated quality	Rating
Sun (2012)	Content	Valence	Platform	Amazon	Average rating	Mean rating	Rating
Adjei, Noble, and Noble (2010)	Content	Valence	Brand community	Brand community	Valence of information exchanged	Positive/negative Pleasing/displeasing Upsetting/not upsetting	Rating
Chintagunta, Gopinath, and Venkataraman (2010)	Content	Valence	Review site	Yahoo! movie website	Variance	Inverse of variance in ratings	Variance
Tirunillai and Tellis (2012)	Content	Valence	Platform	Web	Difference in ratings	Difference in mean rating of reviews	Rating
Tirunillai and Tellis (2012)	Content	Valence	Platform	Web	Difference in pos chatter	Difference in number of reviews	Count
Tirunillai and Tellis (2012)	Content	Valence	Platform	Web	Difference in neg chatter	Difference in number of reviews	Count
Moe and Trusov (2011)	Content	Valence	Web retailer	Bath equipment	Change in variance of rating	Variance of ratings	Variance
Moe and Schweidel (2012)	Content	Valence	Platform	BazaarVoice	Valence × variance	Daily	Index
Berger, Sorensen, and Rasmussen (2010)	Content	Volume	Review site	Book reviews	Review length	Number of sentences	Count
Chen, Fay, and Wang (2011)	Content	Volume	Review site	Automobile sites	Number of postings	Number of postings	Count
Moe and Trusov (2011)	Content	Volume	Web retailer	Bath equipment	Volume of ratings	Number of ratings	Count
Moe and Trusov (2011)	Content	Volume	Web retailer	Bath equipment	Change in volume of ratings	Number of ratings	Count
De Vries, Gensler and Leeflang (2012)	Content	Volume	Facebook	Brand pages	Number of likes	Number of likes	Count
Netzer et al. (2012)	Content	Volume	Platform	Sedan auto forum	Number of threads	Number of threads	Count
Tirunillai and Tellis (2012)	Content	Volume	Platform	Web	Difference in volume of chatter	Difference in number of reviews	Count
Moe and Schweidel (2012)	Content	Volume	Platform	BazaarVoice	Volume × variance	Daily	Index
Moe and Schweidel (2012)		Interaction	Platform	BazaarVoice	Valence × volume	Daily	Index
Stephen and Toubia (2010)	Network structure	Size	Shop network	Marketplace	Marketplace size	Number of shops	Count
Katona, Zubcsek, and Sarvary (2011)	Network structure	Size	Social network	Major EU network	Network size	Network size	Count

Netzer et al. (2012)	Network structure	Size	Platform	Sedan auto forum	Number of unique users	Total	Count
Aral and Walker (2011)	Network structure	Size	Social network	Facebook App	Degree	Number of Facebook friends	Count
Katona, Zubcsek, and Sarvary (2011)	Network structure	Size	Social network	Major EU network	Degree	Number of friends	Count
Ansari, Koenigsberg, and Stahl (2011)	Network structure	Size	Social network	Artist, R&D	Standard indegree		Count
Ansari, Koenigsberg, and Stahl (2011)	Network structure	Size	Social network	Artist, R&D	Standard outdegree		Count
Trusov, Bodapati, and Bucklin (2010)	Network structure	Size	Social network	Panel	Fraction of influential friends	Percentage of influential friends	Percentage
Katona, Zubcsek, and Sarvary (2011)	Network structure	Size	Social network	Major EU network	Average total degree	Av. number of friends of friends	Count
Stephen and Toubia (2010)	Network structure	Size	Shop network	Marketplace	Network links	Number of links in shop network	Count
Stephen and Toubia (2010)	Network structure	Size	Shop network	Marketplace	Dead ends	Total number of dead end shops	Count
Ansari, Koenigsberg, and Stahl (2011)	Network structure	Connections	Social network	Artist, R&D	Multiplexity	Combination of correlation parameters	Latent Construct
Ansari, Koenigsberg, and Stahl (2011)	Network structure	Connections	Social network	Artist, R&D	Homophily	Similarity on observed & unobs. char.	Latent construct
Ansari, Koenigsberg, and Stahl (2011)	Network structure	Connections	Social network	Artist, R&D	Reciprocity	Combination of correlation parameters	Latent construct
Ansari, Koenigsberg, and Stahl (2011)	Network structure	Connections	Social network	Artist, R&D	Selectivity	Combination of correlation parameters	Latent construct
Ansari, Koenigsberg, and Stahl (2011)	Network structure	Connections	Social network	Artist, R&D	Transitivity	Stochastically modeled latent closeness	Latent construct
Mallapragada, Grewal, and Lilien (2012)	Network structure	Distributions	Platform	Platform	Degree centrality	Number of existing projects connected to any given person	Count
Ransbotham, Kane, and Lurie (2012)	Network structure	Distributions	Platform	Wiki	Global network (closeness) centrality	Node's avg distance to all other nodes in the network	Number
Ansari, Koenigsberg, and Stahl (2011)	Network structure	Distributions	Social network	Artist, R&D	Generalized exchange	Combination of correlation parameters	Latent construct
Ansari, Koenigsberg, and Stahl (2011)	Network structure	Distributions	Social network	Artist, R&D	Bidirectional link intensity	Weighted information exchange	Count
Katona, Zubcsek, and Sarvary (2011)	Network structure	Segmentation	Social network	Major European network	Average clustering	Average links between friends' networks	Count
Liu-Thompkins and Rogerson (2012)	Network structure	Segmentation	YouTube	YouTube	Subscriber network connectivity	Number of links in first level network in relation to total possible	Percentage
Katona, Zubcsek, and Sarvary (2011)	Network structure	Segmentation	Social network	Major European network	Average betweenness	Min. number of nodes between 2 persons	Count
Mallapragada, Grewal, and Lilien (2012)	Network structure	Segmentation	Platform	Platform	Betweenness centrality	Shortest path in network	Count

1971; see Belk 1975 for an early marketing application). In our framework, marketing inputs (Stimuli) compare to frequently used marketing instruments (e.g., information, advertising, pricing), whereas social media represent the organism (Organism). Managerial outcomes (Response) are either specific (intermediate) success metrics, e.g., for customer relationship management (customer lifetime value; see also Malthouse et al. (2013), for more details) or brand management (awareness, liking; see Gensler et al. (2013)), or general success metrics (e.g., market share, profit; Farris et al. 2006). In this overarching theoretical framework (see Fig. 1) social media constitute a new kind of organism compared to traditional media. Hence, they require a closer investigation.

Above, we define social media as *communication systems that allow their social actors to communicate along dyadic ties*. From this definition we infer the four focal elements of social media for our S–O–R framework: motives, content, network structure, and social roles & interactions. First, actors are the core ingredient of the system as they communicate along the dyadic ties. The communication of each actor is driven by specific *motives*. Second, they communicate with each other along the ties, producing 'user generated' *content* as the emerging literature defines it. Third, the combination of all dyadic ties forms the *network structure* that is the environment for each actor as well as for the social medium as a whole. Fourth, actors not only produce content as they communicate, but also modify, share or simply consume it. Thus, actors share in different types of *social interactions*, and over time, they assume various *social roles*. Now we will particularize each element in more detail, drawing on theoretical considerations as well as the emerging literature on social media. We present and discuss selected social media metrics for these elements suggested by previous empirical research (see Table 1 for a select review of empirical studies that use social media metrics).[1]

Motives

We draw on the Motivation, Opportunity, and Ability (M–O–A) paradigm as elaborated by MacInnis, Moorman, and Jaworski (1991) to illuminate the driving force behind the action of actors in social media: They define motivation as *goal-directed arousal* (e.g., Park and Mittal 1985), i.e., the desire or readiness to process information; they define opportunity as the extent to which distractions or limited exposure time affect actors' attention to a piece of information (e.g., Batra and Ray 1985); and they define ability as an actor's skills or proficiencies in interpreting information given prior knowledge (e.g., Alba and Hutchinson 1987). From a firm's perspective, assessing the motives or why people (re)act as they do appears crucial.

From the recent literature, we identify four contributions that investigate why actors engage in social media (Adjei, Noble, and Noble 2010; Edvardsson, Tronvoll, and Gruber 2011; Eisenbeiss et al. 2012; Seraj 2012). With regard to the identification of motive-related metrics, no other empirical contribution included in our extensive literature review directly measures the motivations of social media usage of its actors. All of the motives suggested and/or empirically investigated by these studies derive from the value created for the participating individuals. Consolidating the collective insights, we subsume them into the motivational structure suggested by Seraj (2012): (1) *intellectual value* stemming from co-creation and content quality (Seraj 2012). This may subsume signification, which Edvardsson, Tronvoll, and Gruber (2011) describe as drawing a meaning from content via interpretative schemes and semantic rules. Such schemes and rules are usually based on values and motivations. Additionally, we subsume the motives of creativity (Eisenbeiss et al. 2012) and uncertainty reduction (Adjei, Noble, and Noble 2010) into this value category; (2) *social value* from platform activities and social ties (Seraj 2012) which also entails domination (i.e., by drawing on unequal distribution of resources like abilities and network ties; Edvardsson, Tronvoll, and Gruber 2011) as well as socializing, escape, and social identity (Eisenbeiss et al. 2012); and (3) *cultural value* which represents the self-governed community culture (Seraj 2012) and subsumes legitimation (i.e., social norms to evaluate other actors' behaviors; Edvardsson, Tronvoll, and Gruber 2011) and "we-intentions" (Eisenbeiss et al. 2012). We add these three dimensions to the 'motives' element in our framework (see Fig. 1).

The findings of Eisenbeiss et al. (2012) underline the importance of accounting for such different motives. Their empirical results show that the lion's share of users engages with social media due to predominantly one of these three motivations, and very few users report multiple motivations. Accordingly, firms need to reflect this heterogeneity when analyzing outcomes from social networks in their managerial dashboards.

Together with selected other framework elements, '*motives*' later inspire our guideline #1 on why brands have to replace control with influence; #3 on why brands may have to learn to embrace adversity under specific conditions; #4 on why quality metrics now matter more; #5 on why transparency may lead to unwarranted feedback-loops on metrics; and #9 on why theory needs to prevail, but pragmatism should escort in social media metric and dashboard setups.

Content

For the structuring of content in social media we draw exclusively on the recent literature. Here, we identify five studies that categorize social media content and relate the different types to managerial outcomes (Berger and Milkman 2012; De Vries, Gensler, and Leeflang 2012; Kozinets et al. 2010; Liu-Thompkins and Rogerson 2012; Van Noort, Voorveld, and von Reijmersdal 2012).

De Vries, Gensler, and Leeflang (2012) analyze how created content drives social media action. They first characterize the content along the dimensions of vividness, interactivity, information, entertainment, position, and valence. They continue to show that these characteristics asymmetrically influence the number of likes and comments. Van Noort, Voorveld, and von

[1] We conducted a review of metrics on social media used in major marketing journals. In total, we screened about 70 articles, mostly from 2010 to 2013. We categorized any social media metric entailed in these studies according to its domain (i.e., motives, content, network structure, and social interactions & roles). We refrained from measuring inputs and outputs that are well known in the business literature, like mailings, advertising or profit and sales, as the focus of this research is on new metrics. A more detailed table is available upon request from the corresponding author.

Reijmersdal (2012) also highlight the importance of interactive content on diverse cognitive, affective, and behavioral outcomes. Liu-Thompkins and Rogerson (2012) extend these findings to YouTube videos. Again, entertainment and educational character drive the popularity and the ratings of videos. Berger and Milkman (2012) investigate which characteristics make online content go viral. They find that content is more likely to viral when it reflects anxiety, anger, or awe, but even more so when it is practically useful or surprising. Accordingly, the valence of content alone is not sufficient to explain its viral spin. Kozinets et al. (2010) categorize content in the context of online word-of-mouth. They identify four different approaches to message conveyance in blogs. These mirror different narrative styles, resulting in different quality aspects of content: evaluation, explanation, endorsement, and embracing. Each of these qualitative styles alters original marketing messages in a very distinct but systematic way, depending on the forum, the communal norms and the nature of the original marketing message.

Taken together, it emerges that content may have three sufficiently distinct aspects. These aspects are (1) *content quality*, subsuming content characteristics (e.g., interactivity, vividness), content domain (e.g., education, entertainment, information), and narrative styles; (2) *content valence*, subsuming emotions (e.g., anger, anxiety, joy) and tonality (e.g., positive, negative); and (3) *content volume*, subsuming counts and volumes. In our review of the literature, we identified 21 empirical studies with 72 employed content metrics: 14 of those metrics assessed content quality; 25 the valence of content; 32 metrics relate to content volume; and 1 metric represents an interaction term between valence and volume (see Table 1 for a selection of such metrics). Taken together, more informative metrics on content often require additional goal-oriented data collection or advanced computational procedures, e.g., on content quality when assessing metrics on production quality (e.g., Liu-Thompkins and Rogerson 2012) or on positive versus negative content valence (e.g., Berger, Sorensen, and Rasmussen 2010). Additionally, social media metrics and subsequently dashboards would need to cover the states, dynamics (e.g., Moe and Trusov 2011; Tirunillai and Tellis 2012), and heterogeneity (e.g., Sun 2012; Zhang, Li, and Chen 2012) in all three aspects.

Together with selected other framework elements, '*content*' later inspires our guideline #1 on why brands have to replace control with influence; #3 on why brands may have to learn to embrace adversity in specific conditions; #4 on why quality metrics now matter more; #7 on why brands need several layers of social media metrics in dashboards to ensure sufficient insights to the social network landscape; and #9 on why theory needs to prevail, but pragmatism should escort in social media metric and dashboard setups.

Network Structure

Social network theory and subsequent network analyses initially took a *relational* perspective of social networks as both are focusing on the ties connecting all the actors. Any observed effects are primarily investigated through the properties of relations between actors, instead of the actors' properties (e.g., Burt 1980). In a first extension, Blau (1974, 1977) suggests a macro-level perspective and describes the collection of actors in a network through a set of multidimensional parameters. Those parameters are either nominal (e.g., age) or gradual parameters that rank order members (e.g., income). A striking feature of these parameters is that they are expressed as distributions or dynamics rather than states. Accordingly, when describing a social network the distribution of income (its heterogeneity) is more important than income itself, or in other words, the evolution of the income (and its distribution) is more important than the underlying states. Blau (1977) suggests that inequality in distributions impedes intergroup relations, while heterogeneity promotes it. This hypothesis has been extended by Granovetter (1973, 1983) who explores the "strength of weak ties" in social structures with respect to word-of-mouth or innovations, linking the insights from sociology to the marketing domain. In a second extension, Burt (1980) categorizes models of network structures. He distinguishes network model approaches along two dimensions, the (a) aggregation level of actors and (b) the reference frame within which an actor is analyzed. The aggregation level extends from micro-level (i.e., actor related analysis of ties) via intermediate or meso-level (i.e., multiple actors as subgroups) to macro-level models (i.e., actors or groups as a structured system). In the second dimension, he categorizes network analysis approaches as "relational" when the intensity of actor pairs is the focus of analysis, and as "positional" when all defined relations between actors need consideration to evaluate a relative position in a given network.

Overall, the network structure of a social medium should be described along the following network dimensions (e.g., Freeman 2006; Hanneman and Riddle 2011; Kadushin 2012; Scott 2012):

- Size (e.g., the total number of actors or the degree of locality)
- Connections (e.g., homophily, multiplexity, mutuality, network closure)
- Distributions (e.g., centrality, density, distance, tie strength)
- Segmentation (e.g., clustering coefficient, betweenness).

Table 1 illustrates select metrics for each of these domains. Extant studies mostly use total network size or the degree or size of the network at the individual participant level as a corresponding social media metric. With respect to connections, the study by Ansari, Koenigsberg, and Stahl (2011) serves as an outstanding study illustrating the importance of such measures. Distributions have mostly been measured via centrality metrics, with exceptions like Ansari, Koenigsberg, and Stahl (2011) who also measure the tie strength through intensity metrics. Segmentation is usually captured via common clustering or betweenness metrics (see Table 1 for a selection of metrics across all domains). Some of these measures are new and some of them also partially account for actor or content characteristics (e.g., homophily, multiplexity), while others focus on technical relational or positional perspectives (e.g., degree, centrality). Following network theory and its model structures, these network dimensions may help in describing relational or positional perspectives at all network levels, i.e., the macro-, meso-, and micro-levels of a network (e.g., Burt 1980).

Together with selected other framework elements, '*network structure*' later inspires our guideline #2 on why processes and distributions are key in social media; #4 on why quality metrics now matter more; #6 on why social media metrics often need a balancing counterforce in social media dashboards; #7 on why brands need several layers of social media metrics in dashboards to ensure sufficient insights to the social network landscape; #8 on why importance prevails compared to urgency of action; and #9 on why theory needs to prevail, but pragmatism should escort in social media metric and dashboard setups.

Social Roles & Interactions

We previously elaborated on three poles of our holistic framework: the *motives* of actors as the driving force of action in social media; the *content* that travels along the dyadic ties; and the *network structure* that describes the underlying social infrastructure. Against this backdrop, we observe social interactions taking place. Each actor not only receives and simply forwards content, but may also perceive, evaluate, and subsequently alter and augment it in many ways. Consistent and sustained actions on specific content may earn actors certain social roles within their network. Interactionist social theory defines *social roles* as neither given nor permanent. A social role is continuously mediated between actors in a social network, especially by observing and copying the behavior of others. That happens in an interactive way, i.e., any role is contingent on the other actors oscillating between cooperation and competition. As social roles are dynamic concepts, they are constantly shaped through the process of *social interactions*, which sociology defines as a dynamic, changing sequence of social actions and communication between individuals or among groups. However, as all actors constantly try to define their current situation, they strive for a superior social role and attempt to sign up other actors in support (e.g., Mead 1934).

Attribution theory may help to explain why social interactions and social roles are positioned at the intersection of the three poles of the framework. In essence, attribution theory posits that actors in social networks strive to assess the true properties of objects of interest which, for instance, could be properties of actors, content, or ties. To ascertain the external validity of their perceptions, actors analyze multiple subsequent observations that they make. Accordingly, they attribute outcomes or properties either toward (1) a piece or type of content (i.e., entity dimension), (2) an actor and his motivational profile (i.e., person's dimension), or (3) the context described by *time and modality* (e.g., Mizerski, Golden, and Kernan 1979, p 126). As such, attribution processes are assumed to instigate *social interactions* such as information-seeking, communication or persuasion (Kelley 1967, p 193). Any such attributions are made on a background of antecedents like the motivation of the actor herself, her prior beliefs, and prior information received (e.g., Folkes 1988). Attributions are also governed by informational dependence, in particular with respect to the ties of an actor in the social network. Informational dependence may subsequently result in social influence or assigned social roles (e.g., Kelley 1967). Hence, the particular impact, subsequent modification, and further sharing of a piece of content received by an actor may depend on her own as well as the sender's suspected motivations, the type of content and the way it is framed, the (social role or) position of the sending person in the network as well as who else received it at the same time. Hence, at the intersection of the three poles we observe social interactions which lead to the assumption of social roles over time, and which themselves feed back into motivations, content, and network structures.

The theoretical foundation of social interactions and roles is mirrored in recent contributions on social media. With respect to motivations, Edvardsson, Tronvoll, and Gruber (2011) suggest that social roles are the result of interacting forces that draw on motives and network structure. Even theoretical models on network structure show that the structure of social networks can depend on the distribution of motivations, so the resulting structure is in effect endogenous (e.g., Ballester, Calvó-Armengol, and Zenou 2006; Galeotti and Goyal 2010). Within the content domain, Kozinets et al. (2010) suggest that altering of (marketing) messages depends on the co-producing actors, social norms (i.e., their motivation) and the original content itself. Hence, content is an input as well as an output to social interactions. From the network perspective, several sources (see above) suggest that trust, and in turn the social role of an actor within her social network, is not only driven by network structure, but may also be driven by the repeated reception of consistent content from different actors as attribution theory posits. Zhang and Zhu (2011) show that a decreasing network size and content volume will have a negative impact on users' incentives to contribute in social media, again underlining interaction effects between all elements of the framework. Other studies show the positive effect of network structure (i.e., higher closure coefficients and more redundant ties) and homophily (i.e., similar neighbors in the network) on behavior diffusion (i.e., in our framework social interactions; Centola 2010, 2011). Taken together, this supports the distinction of the fourth element as a separate entity in our framework.

The literature on social roles and social interactions is rich in diverging approaches. Social theories suggest family, tribal or functional roles as social roles that an actor can take, whereas the cited interactionist social theory argues that social roles may be in flow and contingent. In the context of social media we are currently aware of promising (e.g., Edvardsson, Tronvoll, and Gruber 2011; Seraj 2012), but not yet consistent research results on social roles of actors. This constitutes a significant research gap. With respect to social interactions, social theories suggest characteristics of social interactions (e.g., solidary, antagonistic, mixed, intensity, extension, duration, organization), but do not provide explicit classifications. After an extensive literature review and searching the web for various usage classifications on social media activities, we consolidate several practitioner analyses on social media to arrive at four social interactions: sharing, gaming, expressing, and networking. These are currently the dominant social interactions taking place on social media. Again, we suggest this as an emerging area for further research.

Together with selected other framework elements, '*social roles*' later inspire our guideline #1 on why brands have to replace control with influence; #3 on why brands may have to learn to embrace adversity in specific conditions; #4 on why quality metrics now matter more; #5 on why transparency may lead to unwarranted feedback-loops on metrics; #8 on why importance prevails compared to urgency of action; and #9 on why theory needs to prevail, but pragmatism should escort in social media metric and dashboard setups.

'*Social interactions*' also help in deriving guidelines #4, #8, and #9, but are not predominantly involved for guidelines #1, #3, and #5. But they are crucial in assessing guideline #2 on why processes and distributions are key in social media; #6 on why social media metrics often need a balancing counterforce in social media dashboards; and #7 on why brands need several layers of social media metrics in dashboards to ensure sufficient insights to the social network landscape.

Framework Summary

Combining all four elements (motives, content, network structure, and social roles & interactions) with their different aspects results in our suggested framework depicted in Fig. 1. Within any social medium, all four elements interact continuously, altering and reinforcing each other as in a living organism. Participating individuals are heterogeneous, and dynamics are inherent in all elements as network theory and interactionist social theory suggest. As individuals may participate in several social media like Facebook and Twitter, any social network may not be fully understood in isolation. Due to the egalitarian and networked character, the process of message altering (and delivery) throughout a social network is highly nonlinear. Hennig-Thurau et al. (2010) recently describe this effect as marketing "pinball" (see also Labrecque et al. (2013), on consumer power). The framework also underlines the definition of social media based on social interactions and interactivity as distinguishing features: Any reaction to marketing input will be immediate, multiway, and contingent. Hence, any dashboard first requires metrics that sufficiently capture the four elements of our suggested framework, before these metrics themselves can be related to marketing input and outcomes.

Guidelines for Designing Social Media Metrics in Dashboards

Constructing sensible social media metrics and subsequently productive dashboards require a holistic approach. Our theoretically derived framework guides managers and researchers to understand and capture the relevant phenomena in appropriate metrics. We refrain from reviewing marketing input and outcome measures as these are commonly known. A dashboard, however, requires linking marketing inputs via social media metrics to outcomes that correspond to the goals of an organization. Given the variety of organizations and social media, there is no such thing as "the" dashboard or metric for social media. Every organization needs to choose the appropriate metrics for its specific dashboard tied to its organizational goals, structure, social media selection, etc.

However, the framework and its theoretical foundation yield some fundamental guidelines that organizations should observe when designing social media metrics and dashboards. Each of them is inspired by a different combination of interacting framework elements as we foreshadowed above. As these guidelines are flowing from the underlying nature of social media, they should represent some general insights that carry validity for any kind of existing social media as well as those yet to emerge. They should help organizations to avoid some often observed pitfalls and result in finely balanced dashboards enabling managers to successfully navigate their social media space (see Fig. 2).

Guideline #1: Transition from Control to Influence

Control in 'Classic' Media

For brands, social media work differently compared to traditional media. In the traditional media setting, managers and agencies *create and distribute* advertising to consumers. They communicate indirectly via uni-directional media. All consumers who watch TV in a given hour or read a certain magazine are to some extent exposed to this communication. Hence, managers have control and authority over brand communication. They also have a simple S–O–R scheme to test, where they can track the effectiveness of their input to higher awareness. This measurement is not transparent or observable to the public. In sum, traditional media are rather controlled, inside-out talking media and offer the possibility of publicly unnoticed success measurement. The following three insights are predominantly derived from the '*motives*', '*content*', and '*social role*'-framework elements.

Loss of Control in Social Media

In social media, brands and their managers are just *equal* actors in the network. A frequent analogy used is the transformation of brand managers from a lab scientist into just another lab mouse. For instance, managers can still post content, e.g., advertorial videos or comments, but whether someone dares to notice is decoupled from the consumption of the medium. When the piece of *content* is not of interest to the initially linked actors in the personal network of the brand, i.e., does not fit the *motives* of directly linked consumers, the content will neither be read nor altered, and what is even worse in social media, not be shared with third parties. In essence, sustained reach cannot be bought like in traditional media. And if original marketing content addresses the motives of its target population, actors will engage and may alter or augment that original marketing message. Hence, reach in social media will only come through the action of other users in the network, and the price to pay for that reach is a probably altered and augmented marketing message from a 'classic' advertiser's point of view. This has profound implications for all major marketing activities, e.g., brand or customer relationship management (see Gensler et al. (2013); Malthouse et al. (2013), for respective extensions). As a consequence and in comparison to traditional media, social media advertising strips managers of their control over reach, and along with reach, their control over the ultimate message conveyed.

Influence in Social Media

In order to build and maintain influence in social media, a brand needs to identify and attract a group of users that engage with the brand and subsequently act on its behalf. This group of users need not be large, but rather influential; meaning they have certain *social roles* within their networks that allow them to

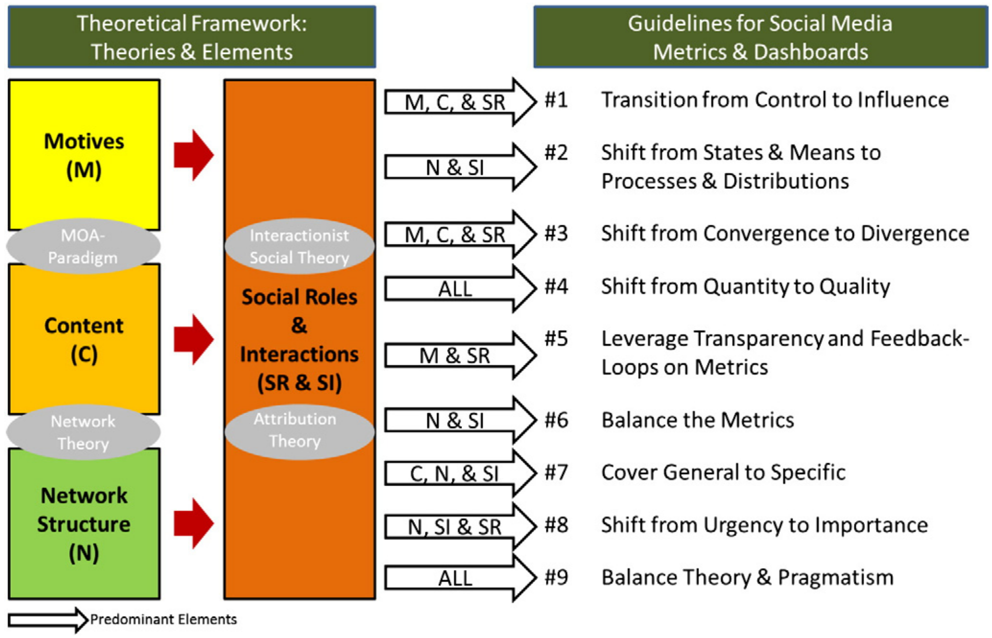


Fig. 2. Linking theories & framework elements to guidelines.

influence other users' perceptions (see section on Attribution Theory). But (influential) users will only engage if it suits their *motives* and *social roles*. Assessing these motives usually requires a dialogue between the brand and the actors in the network. And as a dialogue in turn requires bi-directional communication, above all an organization needs the ability to listen. Such listening, understanding, and responding to an individual actor changes the concept of traditional media in another meaningful way: previously pure inside-out communication turns into balanced outside-in communication. Accordingly, brands need to build up capabilities to listen and respond at the individual consumer level. They also need to develop appropriate metrics that monitor the listening and responding performance in the dashboard. Especially for listening, it can be challenging for brands to find the right metrics that are complete as well as diagnostic, e.g., to find the appropriate combination of keywords to search for (compare metric definition above). In comparison, traditional media metrics are mostly made for inside-out communication. Additionally, firms need metrics to capture the continuous assessment of motives across their follower base as well as at the higher network level. All new metrics for listening, understanding, and responding need to be incorporated into a brand's dashboard.

Illustrating the Different Paradigm

Overall, the dialogue nature of social media propels brand communication from a patriarchal to a participatory paradigm. Congruent with this change, brand managers move from a position of control in classic media to one of influence in social media: Only if advertising content satisfies the *motives* of directly linked actors, will they share it with third parties and so build the overall reach that the brand pursues. In classic media, managers would assess the reach of a media vehicle in which they advertise a certain message. In social media that concept does not apply as managers have no control over the distribution of a message they send. And the direct number of followers is a poor proxy if these followers are not engaged or have small networks. Rather, managers need to assess the second and third degree reach of their core network to assess the *potential organic reach* of any message. This organic reach need not correspond with the number of core followers, as a few highly influential and engaged users may overcompensate for a large number of hardly engaged followers with smaller networks and less clout. This kind of metric is not known in the traditional media environment, but essential in social media and needs to be included in corresponding dashboards.

Another consequence of this participatory nature is that discourse may take place without the brand as an actor (see Gensler et al. (2013); Labrecque et al. (2013), for extensions). The extreme form of this would be so-called "shitstorms", i.e., bad communication spiraling out of control of a focal brand. Hence, social media dashboards need metrics that not only listen to personal networks of brands, but also to the noise across social systems. A German example may illustrate this. A large coffee chain used classic and social media to advertise organically grown coffee beans. After a couple of months, an influential user noticed and communicated that the advertising spots actually featured white farm owners with colored people working for them, implicitly linking the plot of the spot to resemble inappropriate and stereotyped social conditions. Although the coffee chain actually explains in its blog that the white 'owner' is indeed renting the place and treating her workers exceptionally well for local standards, the coffee chain had no means to confront its accusers. It realized the issue too late (after the user's allegation went viral) and it initially relied on its large, but disengaged follower base, only to discover the uselessness of a large follower network when it really needed help spreading the correct information. This example underlines the requirement for several metrics in dashboards that monitor particular levels of the network with respect to listening, understanding, responding, and organic reach.

Finally, managers should be aware that everything they do in terms of listening, measuring and responding is often transparent in the social network, i.e., from likes to levels of activity, is not only known to the managers, but to all "mice in the lab." We add this here for closure but pick this issue up in detail under guideline #5.

Guideline #2: Shift from States & Means to Processes & Distributions

States in 'Classic' Media

For traditional media, decision-makers focus on metrics that express media performance in states rather than processes or distributions. For instance, they measure the state of awareness, purchase intent, etc. However, social media are based on networks, and network theory predicts that distributions, (i.e., heterogeneity and dynamics) are more important than states when describing social systems (see the theoretical discussion above). Accordingly, this guideline is predominantly inspired by the '*network structure*'-element of the framework, with the '*social interaction*'-element in a major supportive role. Additionally, we also refer to *motives*, *content*, and *social roles*.

Processes and Distributions in Social Media

The dynamics of social media have four important facets. First, it is the *growth or decline* in numbers that is a relevant signal. For instance, a brand page can be very popular in terms of total likes (a state), but if growth is slowing over a certain time — and this fact is transparent to all users in the network — the relevance to other users is also declining despite the high number of followers. Hence, often the 1st or 2nd derivative of a state may be a more important metric to track in dashboards than the actual state (e.g., Tirunillai and Tellis 2012).

Second, these processes may exhibit certain *path dependencies*. Moe and Schweidel (2012) highlight the path dependency of online reviews: If the initial review is a 5-star, subsequent users that want to differentiate themselves (i.e., their underlying *motive*) can only do so by adding worse reviews. In course, the average evaluation may deteriorate not because of a deficient product, but by users differentiating themselves. Given a median evaluation, its evolution also crucially depends on the heterogeneity or distribution across the user base, e.g., when a core group of activists (a *social role* embraced by and assigned to them in the network) emphasizes negative ratings.

Third, the *dynamic* trend in communication activity is more relevant than the state. This insight also follows from *network* theory in conjunction with our pivotal framework element on *social interactions*. Thus, it is the dynamics or intensity of *social interactions* that qualify a link or actor more than its mere presence (which is a state). Traffic generated by actors as well as traffic on links can be easily measured online. The challenge for a brand is to filter out the right nodes and links to watch from among the plethora in the network, and to incorporate those in the dashboard (which links back to guideline #1). However, current social media tracking systems often allow for the real-time tracking of prominent posts or tweets. And some new scores like the EdgeRank (in Facebook) or the KloutScore (across media) assess the time-dependent importance of all network actors, although these metrics partly lack the diagnostic value they should carry as its details of calculation are unknown (see metric definition).

Fourth, social media exhibit *memory effects or feedback loops*. Many brands use non-core brand related activities to generate high numbers of likes or followers (a state), for example via sweep-stakes. As attribution theory suggests, such activities may attract people that are more interested in sweep-stakes than the core brand's values (see framework section on Social Roles & Interactions above). Hence, these followers become inactive once the sweep-stake is over. However, in social media such remnants of previous activities result in dead-weight for future marketing activities or the nurturing of a truly loyal and engaged fan base. A leading German online retailer once conducted a crowd sourcing model competition for its advertising campaign in social media. The campaign gained momentum and visibility, but failed to engage users permanently at the brand's fan page, rendering most 'likes' inactive. Nowadays, these high numbers of inactive users drag the fan page's importance in all leading activity scores (like Edgerank), substantially aggravating current marketing efforts and effectiveness.

Network theory suggests that *distributions* may be more important than states in social media. This insight is supported by recent findings in the literature: Sun (2012) examines the informational role of product ratings. The study shows theoretically as well as empirically with data from Amazon that a higher standard deviation lifts a product's relative sales rank only when the average rating is below 4.1, which holds for 35% of books in her Amazon sample. Moe and Schweidel (2012) highlight the dynamics of online reviews based on underlying heterogeneity. In essence, customer bases with the same median evaluation may evolve in substantially different ways when a core group of activists emphasizes negative ratings. In sum, metrics that capture such network dynamics *and* the underlying heterogeneity in social media are crucial ingredients for social media dashboards.

Guideline #3: Shift from Convergence to Divergence

For traditional media, organizations thrive on convergence toward better states reflected in metrics. For instance, the higher "brand sympathy" across the population the better. In social media, however, divergence is not always bad. We derive the two aspects related to this guideline predominantly from the framework elements '*motives*', '*content*', and '*social roles*'.

In contrast to convergence efforts offline, certain brands may thrive on adversity in social media as differentiation increases. This reinforces the identification of its core users whose *motive* is 'to be different,' and for whom the brand is a means to this end. One example may be Abercrombie & Fitch which was the target of a social media campaign by users based on a seven-year-old quote of its CEO stating that the brand is indeed "exclusionary." The resulting adverse reaction toward the brand in social media may nevertheless have improved the identification of its core brand users. Additionally, whereas divergence and subsequently lower product evaluations may trigger substantial marketing audits offline, it may be a naturally evolving phenomenon in social media online (e.g., Chen, Fay, and Wang 2011; Godes and Silva 2012; Moe and Trusov 2011). In sum, when a brand thrives on differentiation, organizations may need adequate metrics to measure both in their dashboards, the adversity as well as the positive sentiment (also compare earlier elaborations on metrics for capturing the dynamics and heterogeneity of the '*content*' element in the framework section).

Another associated aspect is that in social networks it matters who says something to whom in what context. This is related to *social roles* in the network as well as the contingency aspect of attribution theory. Accordingly, the objectivity of offline "means" (where managers evaluate answers to specific questions) is replaced by a qualified inter-subjectivity. In effect, convergence becomes rather situation or state dependent. This can be explained by looking at hotel ratings: If a young person was looking for a party hotel and had fun during the holidays, he or she may give a great review. However, an older couple looking for rest will evaluate the same hotel very negatively for the noise they had to endure. The mean or converged assessment will be senseless without accounting for the actors' *motives*, the *content* perspective of evaluation, and the targeted network population. Hence, metrics in dashboards not only need to account collectively for heterogeneity (see comments on metrics for 'content' in the framework section above), but especially with respect to *content* also need to assess contingency aspects. These contingency "keywords" for new metrics in dashboards have to be defined for each brand in its individual context.

Guideline #4: Shift from Quantity to Quality

As we stated above, states and quantities are usually key in traditional media. We also highlighted previously that dynamics in the form of intensity on nodes and links are key rather than the mere existence of nodes and links. At this point, we drive this insight even further and qualify intensity in more detail. In essence, we refer to the engagement levels of actors expressed via *social interactions*, which are tied to *motives*, *content*, and *social roles* within the *network structure*. Above we mention that a high number of 'dead likes' is counterproductive when building a loyal base of followers. Hence, beyond simple 'talk abouts' (mentioning of keywords or brands), many social media dashboards measure different types of *social interactions* and categorize them by the associated level of engagement, e.g., a 'like' has less value than a 'comment' or a 'share' and derives a correspondingly lower score (see buzzrank interaction rate in Fig. 3 for an example). EdgeRank and Kloutscore are similarly constructed, but at the individual level (see Fig. 4). Such metrics should be included in dashboards, however, they lack the transparency in calculation that the buzzrank ratio provides (see metric definition) and are prone to biases (see guideline #5).

It is intriguing that such "engagement" levels are similar to what marketing research predicts for theoretically derived involvement aspects that drive consumer actions. In a way, this provides an ex-post theoretical foundation for these metrics (see metric definition). For instance, Arora (1982) distinguishes three different levels of involvement — situational involvement, enduring involvement, and response involvement — and analyzes their internal structure. Situational involvement is casual and pertains to time and situation, whereas enduring involvement depends on experience with a matter and its relationship with the actor's value system (or motives in our framework). Response involvement finally arises from enduring involvement in conjunction with complex cognitive and behavioral processes. In social media, higher engagement — or respective involvement — levels are crucial for generating sustained traffic and dialogue. In contrast, for many brands we currently still observe sweep-stakes for generating followers or posting unrelated questions to generate traffic in an attempt to boost static numbers. But as we discuss and show above, many non-authentic or brand-unrelated marketing actions may come back to haunt managers in the long-run. Developing and employing adequate metrics to measure engagement levels of consumers — as well as their evolution and heterogeneity — will drive brand managers to more sincere and sustained modes of interaction, i.e., higher quality contacts. Such highly engaged fans, and not necessarily high numbers of them, are crucial in building sustained and authentic reach in social media. And in contrast to awareness levels in traditional media, these engagements cannot be "bought" in instances but need consistent nurturing over time. If these engaged actors also play relevant social roles in the network, they will also be the best defense in case of "shitstorms" (see above) when a brand itself can hardly do the right thing, but needs advocates to speak on its behalf. Additionally, the value of engaged users is not restrained to communication efforts of a brand, but may be used to improve the brand's services or products. Deutsche Telekom and Deutsche Bahn both recently established service centers where engaged users may support the staff in handling customer inquiries. Fiat Brazil went even further and involved engaged users in the concept testing of a new car (Fiat Mio crowdsourcing). They did not only pursue this user integration online, but interested consumers could also visit the firms test lab or open production facility in Sao Paulo. Accordingly, appropriate *quality-based metrics* should be preferred over sheer volume numbers when constructing social media dashboard metrics.

Guideline #5: Leverage Transparency and Feedback-loops on Metrics

In traditional media, the success measurement of marketing actions is often not important to recipients and hidden to the public eye, i.e., the act of measuring is typically unobserved by the recipients of advertising communication. That is different for important metrics in social media, where most measurements are transparent or known to the wider audience. This transparency has some far reaching implications for crucial metrics if they are also important to users.

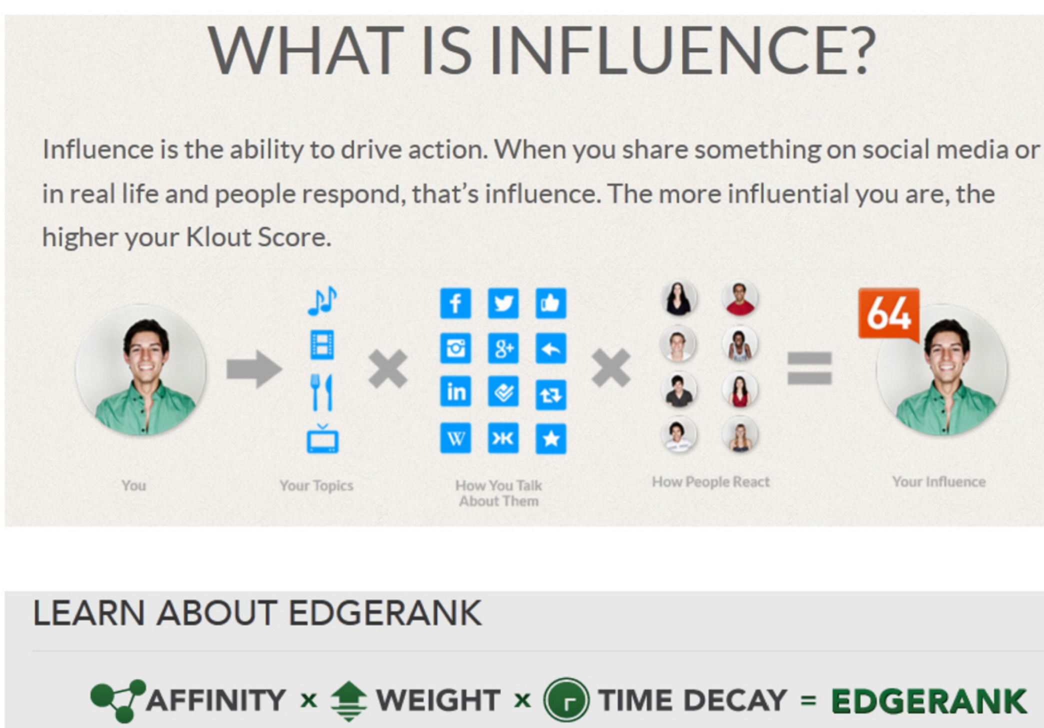
It is known in social sciences as well as physics (Heisenberg's uncertainty principle) that as you try to measure something, you may alter its state and/or dynamics. We observe such phenomena in social media when *social roles* in networks and underlying *motives* — i.e., profits, social, intellectual, or cultural value — are tied to certain metrics. Just think of KloutScore, EdgeRank, Google-Rankings or YouTube-Rankings, which measure a user's

Overview July 2012

Value / KPI	This month	Last month	Δ Changes *(sum)*	Δ Changes *(percentage)*
Number of fans at the end of month	357.536	299.032	58.504	19,56
Talk About (monthly unique users)	110.139	96.342	13.797	14,32
Talk About fan ratio (talk abouts / fans), monthly average	30,80%	32,21%	-0,0141	4,39
Impressions of own postings (26 Postings)	5.956.364	22.971.470	28.037.858	74,07
Reach monthly (number of monthly unique user (organic))	370.972	320.763	50.209	15,65
Number of fan interactions (Postings, Comments, Likes and Shares)	69.835	58.352	11.483	21,13
BuzzRank interaction rate (Value of Likes x 1, Comments x 2, Shares x 3 / Fans x 100)	26,39 %	24,57%	0,0182	7,41

Fig. 3. Excerpt of KPIs from a social media dashboard (Buzzrank 2012).

influence within or across social media. Fig. 4 illustrates how these dashboard metrics are constructed. As the underlying basic rules are transparent, users (collectively) find out by trial and error how they actually work: they simply observe their own as well as other people's behavior and the subsequent result in such metrics. Hence, users start to play such scores when they are important to them. That helps them to attain *social roles* they aspire to while benefiting underlying *motives* such as personal earnings from brand endorsements. As a consequence, any such metrics will be gamed in social media, often rendering them



Sources: http://klout.com/corp/how-it-works; http://edgerankchecker.com/

Fig. 4. KloutScore and EdgeRank metrics.

distorted from inception. And again, *motives*, *content*, *network structure*, and *social roles* from the framework (see Fig. 2) interact to produce such results.

Guideline #6: Balance the Metrics

In traditional media, we often observe that single metrics sufficiently capture the underlying phenomena, like awareness or purchase intent. Social media are different as we pointed out earlier. Metrics for social media most often need an accompanying metric in dashboards as a counterforce that keeps it in balance for a consistent continuing interpretation by managers (see metric definition). To illuminate this need we refer to two previous insights as well as the shifting base phenomenon. These insights are predominantly based on the framework elements '*network structure*' and '*social roles and interactions*'.

Balancing for Metric Gaming

The previous guideline suggests that important metrics will be gamed by users if they are also important to them. This often renders them distorted from inception. The best remedy to keep such numbers from being skewed too much over time is to construct a second metric in the dashboard that penalizes obviously 'fake' or abnormal engagement in postings or other interactions on the brand's fan page.

Balancing Quantity and Quality Metrics

In guideline #4 we suggest that metrics on states alone are not informative, and that metrics capturing dynamics and heterogeneity are of higher importance in *networks* as theory posits. But the latter metrics alone will not suffice in dashboards either. They need to be augmented or balanced with each other as well as with quantity metrics to describe the social network. The exemplary social media report in Fig. 3 demonstrates how the quantity of total fan base (state) is augmented by growth numbers (dynamics). Then these two metrics are accompanied by quality numbers on 'talkabouts', total as well as its growth. Both again are set into relation with each other through intensity measures (*social interactions*) like 'talkabout/fan', again as a state as well as dynamics. Finally, metrics on the corresponding distributions across the fan page population would complete the high-level management report. This underlines that multiple balances need to be woven into social media metrics and dashboards. What is more important, pushing a single metric alone in disregard of the other aspects will result in unsustainable growth that punishes the brand in the long-run.

Balancing for Shifting Bases

Additional aspects of this rule refer to the consistency and reliability of metrics over time (see metric definition). For example, social *networks* are always in flow and change their size, composition, usage levels and structure like a living organism as they evolve. Hence, over time any metric that is employed in dashboards may deteriorate in consistency as its base shifts, adaptations are made (e.g., inclusion of a new social medium in KloutScore or changes to EdgeRank calculations). Especially for new social media, early stages of diffusion inherently bias comparisons with later stages. For example, heavy users of social media tend to adopt earlier than people with lower usage. Accordingly, average usage time may eventually go down over time as more people join these media. These dynamics should hold at all levels of analysis, from the total network down to brand hubs within those media. In comparison, if one assigns a sub-section of the dashboard to the brand's activists (a *social role*) then these metrics should be relatively comparable over time even as the number of low involvement users keeps growing. Hence, we suggest constructing metrics that account for underlying dynamics and heterogeneity through base shifts or correct them for later changes when long-term evaluations are made.

Guideline #7: Cover General to Specific

This guideline encourages managers and researchers to take a bird's eye view of social media while drilling deeper into the matters that require measurement via metrics. Again, such metrics jointly provide a holistic picture in a brand's dashboard. We exemplify this guideline for metrics in dashboards in three instances, namely the view across the landscape of relevant social media, the levels to cover within each social medium, and the levels within an important metric domain. The guideline is predominantly inspired by the framework elements '*content*', '*network structure*', and '*social interactions*'.

Metrics Across Social Media

The brand's metrics jointly need to cover all relevant social media for an organization in the dashboard. On the one hand, consumers may use specific platforms for specific *content*, e.g., Twitter to complain (as they desire a fast company reaction), Facebook to boast about successful purchases (as it only goes out to close friends; see also Yadav et al. (2013), on social commerce) and Instagram to combine brand visuals. These social media may also have different characteristics that require different metrics in the dashboard, as Twitter is an asymmetric (1:n) social medium compared to Facebook which is symmetric (n:n). On the other hand, users are active across social media and subsequently one can regularly observe spillovers, e.g., from Twitter to Facebook activity and vice versa. Both specific and spill-over effects encourage managers to account for both in (social media) dashboards, general metrics at the meta-level across social media (e.g., Kloutscore), and specific metrics that reflect the particular nature of any social medium (e.g., Edgerank).

Metrics Within a Social Medium

Additionally, the guideline refers to the level of measurement within each social medium. As *network* theory suggests, there are no metrics that cover all levels of a network, i.e., from the specific micro- via the meso- to the general macro-level. Neither does a metric capture the relational and positional view of a network simultaneously. The same holds for the analysis at different levels of aggregation for *content*, *motives*, or their interactions in terms of *social roles*. As dynamics and heterogeneity are usually relatively high in social networks, any dashboard needs several layers of metrics that can be combined for specific analysis at specific aggregation levels. Hence, many specific questions may require tailored approaches to measurement through an adequate combination of metrics in a dashboard.

Levels of a Metric Domain

We also urge managers to account for different levels of important aspects like engagement in the dashboard. Engagement, which manifests itself in *social interactions*, can take different levels of intensity as the research on involvement (e.g., Arora 1982) suggests. According to that research one needs to distinguish at least three levels, which can manifest themselves as depicted in Fig. 3 in the buzzrank interaction rate (last row) from likes via comments to shares. Although they are combined here at the overall dashboard level into a single weighted engagement metric, each level is captured separately to inform the overall volume as well as the respective underlying distribution and evolution per instance over time. This detailed view is required as brands need a healthy distribution across these levels, i.e., too many 'likes' without 'comments' and 'shares' are not sufficient to build reach, as is having too many 'shares' within a small community of 'likes'.

These three major aspects of the guideline particularly support the requirement for social media metrics to provide completeness and sufficient diagnostic value (see metric definition).

Guideline #8: Shift from Urgency to Importance

Social media are living organisms. Accordingly, dashboards will always keep on blinking in real-time as '*network structure*', '*social roles*', and '*social interactions*' affect each other. Deviations, even substantial ones, are the rule rather than the exception. Organizations that are used to traditional media are often overwhelmed by the pulse of social media (see also Weinberg et al. (2013), on organizational implications). Knowing about path dependencies and rather quick reinforcement loops may yank their nerves, tempting them to interfere sooner rather than later in user conversations. But as we know from past experiences, interference may be just the wing of the butterfly that was required to send developments spiraling. Hence, when designing dashboards, organizations need to extract the essence of conversations, sentiments, and moods in the audience, but may also determine a *corridor of comfort* which is defined via heterogeneity and dynamics around crucial metrics (also see metric definition). Within this comfort zone, organizations need to let go.

Guideline #9: Balance Theory & Pragmatism

Finally, we suggest balancing theoretical considerations with pragmatism when designing and implementing metrics for social media dashboards. As *all our framework elements* underline, there is a lot that brand managers can take away from existing theories. The diversity of origins of these theories, e.g., sociology, network analysis, marketing and psychology offers a rich pool of insights that may guide them toward sensible metrics. As social media mimic our social systems, the sheer complexity stemming from dynamics and heterogeneity, paired with their egalitarian nature, suggest more than a dose of pragmatism. However, this pragmatism should not lead to complacency in the sense that someone measures what is convenient to measure or what seems handily available (e.g., compare Table 1 for some examples). To some extent, this is natural when a field is still young and emerging. Accordingly, although we encourage as much theoretical consistency or rigor as possible when designing social media metrics, we simultaneously acknowledge that relevance is paramount. It is more important that the effort associated with implementing a metric is balanced by the metric's relevance for the organization, and that metrics are actually tied to managerial implications.

Implications for Practice and Research

Based on our framework and the elaboration of these guidelines we continue to derive implications for managers and provide guidance for future research.

Managerial Implications

Our theoretically driven framework and the generalizing guidelines should enable managers to take a better top-down approach to social media metrics and dashboards. Today, many organizations and agencies use metrics that are either provided by the social network operators or otherwise handily available. These metrics may not be the most relevant ones to inform marketing decisions. Our framework enables managers to first assess what is important to know, and then look for the best proxies available. Even if proxies may not be available, frequent ad-hoc research, e.g. on user motives, may suffice for the time being.

In extension, the framework and its theoretical foundation will also help managers to modify their marketing input (see Gensler et al. (2013), on extensions). In contrast to classic advertising, which is usually not meant for participation (i.e., mostly sharing of videos or simply collecting likes), they need to develop new forms of advertorial content that inspires users to engage, modify and then share it: organizations need to learn to feed and nurture their network base — a living organism. Another implication is that compared to classic advertising media which can be off-and-on at the disposal of the brand managers, this living organism needs constant feeding to survive. Or else, if your brand does not feed it, it turns elsewhere for "food" or produces food on its own, whether you like it or not.

Another striking implication and major challenge for organizations is that user participation will and should not stop with your brand communication. For social media and its egalitarian dialogues, organizations need the capability to listen, digest the information, and respond sensibly. As user dialogues also include logistics, product features and innovation, quality issues and the like, organizations need to reorganize around in-bound and out-bound interfaces (i.e., integrating all in- and out-bound communication channels in service hubs) with almost all internal functions over time (see Weinberg et al. (2013), on more organizational changes). And as organizations integrate their communication interfaces, they will also feel the need for quick and consistent communication response to the plethora of users across all interfaces — in essence, they will sooner or later feel the need for a central content hub that serves all channels on all relevant topics in almost real-time.

Future Research

For academic researchers, our framework, literature review and guidelines set up several areas for future research. First, the conceptual framework we offer is just a start; although it draws on prominent theories from several research domains, however, we should use the opportunity of social networks to search for a unifying theoretical foundation. Also, we need to explore what other theories could add to our understanding of the phenomena in social networks. In particular, we encourage further research on the social roles users assume and the types of social interactions we observe, and how both of these link to actors' motivations, the content, and the network structures. With respect to the network structure, we find the theoretical models predicting the resulting network structure as endogenous (based on prevalent motive structures) appealing. Most research treats it as exogenous. If network structures are in constant endogenous flux, might that open up uncharted territory for completely new dynamic approaches to network modeling?

Second, we offer a general framework and generalizing guidelines on how to construct sensible metrics and subsequently dashboards. As we do not examine the practical usefulness of specific social media metrics, experience tells us that many companies have a bottom-up, data-driven process of collecting and employing such metrics. For instance, small and medium sized enterprises often take at face value the metrics offered for free in, e.g., Facebook Insights or Google Analytics (Wiesel, Pauwels, and Arts 2011). We encourage research on the effectiveness and efficiency of this convenience or availability driven bottom-up approach. The results should be compared to a strategy based on our theoretically inspired top-down approach of first deciding what should be measured and next looking for the best empirical proxies (e.g., De Haan et al. 2013).

Third, our literature review reveals many disjoint studies on selected and specific social media topics. We feel that we are barely scraping at the surface of potential knowledge on social media, which may also reveal a lot more insights for managing other media better. We also suggest that more holistic research covering multiple elements of the suggested framework will be necessary to answer the tough question on social media in a few years, such as: what have we really learned from all these studies?

Finally, we would like to suggest further research on adequate organizational structures and processes that guide organizations in their change process toward seamless dialogue interfaces with social media. Metrics and dashboards are a start, but how can they successfully implement the organizational changes affecting all other aspects of marketing beyond brand communications?

Summary

Social media are becoming ever more ubiquitous and important for marketing purposes. However, social media are substantially different from traditional or other online media due to the network structure and their egalitarian nature. As such, they require a distinct approach to management. A prerequisite for managing social media is their effective measurement. Marketing or subsumed social media dashboards, a sensible collection of key performance metrics linking marketing input via metrics to (financial) outcomes, are the tool of choice — but how should organizations design their dashboard metrics for social media?

Due to the huge variety of (and still emerging new) social media and the specific needs of brands, there is no silver-bullet kind of metric or metric compilation that addresses all requirements for all brands alike. However, due to the shared fundamentals of social media there are common threads that allow at least a unified approach to the construction of appropriate metrics and subsequently dashboards. To help organizations in developing and employing such an appropriate compilation of metrics, we provide them with a tool kit consisting of three novel components: First, we theoretically derived and proposed a holistic framework that covers the major elements of social media, drawing on theories from sociology, marketing, and psychology. We continued to support and detail these elements, namely 'motives', 'content', 'network structure', and 'social roles & interactions', with recent research studies. Second, based on our theoretical framework, the literature review, and practical experience, we have provided nine generalizing guidelines that may prove valuable for designing appropriate social media metrics and constructing sensible dashboards. Third, based on the framework and the guidelines we derived managerial implications and suggested an agenda for future research. We hope that these contributions may provide a reasonable tool kit for research and practice when analyzing, understanding, and managing social media.

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