Evaluation Framework for Social Media Brand Presence

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Auto-ID Labs White Paper WP-BIZAPP-060

December 2012

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Abstract

Social media is becoming an additional marketing channel that could be integrated with the traditional ones as a part of the marketing mix. Although numerous examples of using social media platforms for marketing purposes exist, and despite the various efforts from the companies and the general popularity of the medium, measuring the effectiveness is elusive. An approach towards overcoming these challenges is examination of the activities undertaken by the companies and the consumers' responses to them in the form of measurements and use of analysis tools. To contribute in this direction, we propose an evaluation framework that allows companies to perform social media analytics through continuous monitoring of the content and activities on their social media marketing channels, and to measure the effectiveness of social media utilization for marketing purposes. We describe the specific methods and illustrate the application of the proposed approach using a Facebook brand page case study. Finally, we discuss the benefits it brings to the companies.

Keywords: social networks; Facebook; social media marketing; effectiveness evaluation; social media analytics.

1. Introduction

The emergence of the Web 2.0 has changed the way content is generated on the web. Rather than being just passive consumers, users became active participants by sharing information, experiences and opinions with each other. Social networks (SN), as a part of Web 2.0 technology, provide the technological platform for individuals to connect, produce and share content online (Boyd and Ellison 2008). As such, for brand owners, they offer the potential for (1) advertising - by facilitating viral marketing, (2) product development - by involving consumers in the design process and (3) market intelligence - by observing and analyzing the user-generated content (UGC) (Richter et al. 2011).

The rise and continued growth of SNs have attracted the interest of companies who see the potential to transmit their marketing messages to their customers, enter into a dialogue with them using the word-of-mouth (WOM) principles and to use the SNs to gain a better understanding of their customers (Hanna et al. 2011). As an outcome of this change in the field of marketing, a new phenomenon, generally known as social media marketing (SMM) was introduced.

SMM, a form of WOM marketing, but also known as viral marketing, is intentional influencing of consumer-to-consumer communication through professional marketing techniques (Kozinets et al. 2010). This is not to be seen as a replacement for the traditional marketing techniques but rather as an additional marketing channel that could be integrated with the traditional ones as a part of the marketing mix (Mangold and Faulds 2009). The advantage of this new electronic channel is that it can be used to communicate globally and to enrich marketing toward consumers at personal level (Brandt 2008). Through users' feedback or by observing conversations on social media, a company can learn about customers' needs, potentially leading to involvement of members of the community in the co-creation of value through the generation of ideas (Palmer and Koenig-Lewis 2009).

Companies, across all industries, are starting to understand the possibilities of SMM. They have evolved their customer approach, shifting from the traditional one-to-many communication to a many-to-many approach and offering contact or assistance at any time through SNs such as Facebook and Twitter (Berthon et al. 2007). Using Facebook as an example, this means that companies set up and moderate a brand page, while continuously monitoring the consumers' activities. Still, mere presence on social media platforms is not enough for achieving SMM success (Parent et al. 2011). Today, on account of the newness of SMM, companies experiment with many different forms of interaction (Coon 2010), sometimes with great success, e.g. Nutella found a communication tone that helped it become one of the most successful brands on Facebook (Simply Zesty 2012). By contrast, poor understanding of the medium at Nestlé noticeably damaged the brand when a consumer post about the destruction caused by palm oil forestation was answered by a belligerent company representative, ultimately transporting the resulting discussion to mainstream media (Fournier and Avery 2011). These examples indicate that although many brand pages have already been created, how these pages are being used, what their potential is and how consumers interact, remains largely unknown (Richter et al. 2011).

Examination of the existing examples of activities by companies and the customer's responses to them are of high interest to the moderators of these sites and therefore subject to close examination in the form of measurements and use of analysis tools (Dubach Spiegler 2011). Still, despite the various efforts from the companies and the general popularity of the medium, measuring the effectiveness is elusive (Larson and Watson 2011). Some small cases have been reported, such as the Houston bakery chain that increased customer frequency in their stores thanks to their carefully managed Facebook advertising campaigns (Dholakia and Durham 2010), and an experiment regarding the effectiveness of company-driven WOM communication showed that this can increase sales (Godes and Mayzlin 2009). However, a structured, academic analysis in this field is still outstanding and has yet to be addressed from different perspectives (Richter et al. 2011; Wilson et al. 2012).

To contribute in this direction, we propose an evaluation framework that allows companies to set up and then perform monitoring of the content and activities on their SMM channels. Continuous utilization of the proposed framework could enable early problem detection and reaction from the company in form of strategy adaptation in accordance with the specific characteristics of their brand communities. We illustrate the application of the proposed approach through a case study and discuss the benefits it could bring to the companies.

2. Related Work

2.1. Social Networks and Brand Communities

A SN can be defined as “web-based services that allow individuals to (1) construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view and traverse their list of connections and those made by others within the system.” (Boyd and Ellison 2008) The first recognizable SN that complied with this definition was launched in 1997 under the name SixDegrees.com. Following the period of several smaller launches, the significant expansion of SNs started in 2003 with LinkedIn, MySpace, Flickr, etc., many of which are still in use today. The major leap happened with Facebook in early 2004 (Cassidy 2006). Facebook differed from previous SNs by preventing public access to the user profile pages. Instead, a friend request confirmation was needed to grant reciprocal access to personal data. At the time of writing, Facebook is the largest SN with more than 1 billion active users (Facebook 2012b). With such large numbers of users and a documented loss of consumer trust in traditional advertising (Clemons et al. 2007), it is no wonder that SNs have attracted the attention of advertisers, brand owners and retailers, with predictions of 3.93 billion USD spent for advertising on SNs in 2012 (eMarketer 2011).

SNs are found to have a mediating effect between individuals and society in the virtual world (Wasserman and Faust 1994). As such, they represent a natural technological platform for marketing, providing access to a large number of users, grouped in communities and based on a structured set of social relationships among admirers of a brand, i.e. a brand community (Muniz et al. 2001). According to McAlexander et al. (2002), brand community participation results in a positive effect on consumers’ attitude and attachment to the brand and the company. Furthermore, Ulusu (2010) argues that (1) community members are interested in receiving brand announcements, (2) they feel part of the communities they joined, (3) accept the friendship requests of the brand pages, and (4) value friends’ opinions about a brand.

SNs and Facebook have been studied from different perspectives such as the network structure (Caci et al. 2012), characteristics of the users (Bhattacharyya et al. 2011; Hargittai 2007; Karl et al. 2010), usage patterns (Golder et al. 2007; Lampe et al. 2006) and motivations (Joinson 2008; Raacke and Bonds-Raacke 2008), identity management and self-presentation (Labrecque et al. 2011; Zhao et al. 2008), social interactions (Kostakos and Venkatanathan 2010; Nazir et al. 2008), and privacy and information disclosure (Debatin et al. 2009; Krasnova et al. 2009). In addition, specific usage contexts were analyzed, such as utilization of SNs for knowledge exchange in academia (Ferri et al. 2012), the value of SNs for politics environment (Stieglitz and Dang-Xuan 2012), etc. However, little has been published about the use of SNs in the context of companies, though SNs can be applied in three distinct areas: 1) recruiting and professional career development, 2) relationship facilitation in distributed work contexts, and 3) business-to-customer (B2C) interactions (Richter et al. 2011). It is the B2C interactions that are in the focus of this paper.

2.2. Social Media Marketing

SNs may play a key role in the future of marketing; they may increase customers' engagement, and help to transform the traditional focus on control with a collaborative approach suitable for the modern business environment (Berthon et al. 2012; Harris and Rae 2009; Mangold and Faulds 2009). User participation as a main feature of SNs imposes challenges to the traditional one-way marketing, resulting in companies experimenting with many different approaches, thus shaping a successful social media approach based on the trial-and-error experiences (Coon 2010).

In order to provide insights to practitioners looking to use SNs to benefit their brands, early studies in the field have tried to address the challenges of SN marketing such as aggressive advertisement, lack of e-commerce abilities and invasion of user privacy (Bolotaeva and Cata 2010). In addition, recommendations have been given that companies should avoid over-commercialization and favor transparency instead of trying to fully control their image (Harris and Rae 2009). An inappropriate approach to these challenges could lead to fan loss and exposing the company to the risk of destroying its own credibility (Fournier and Avery 2011). Apart from the challenges, many opportunities have also been recognized, such as raising brand awareness through viral campaigns, product development through community involvement and gathering insights for future steps by analyzing the UGC (Bolotaeva and Cata 2010; Richter et al. 2011).

Based on exploratory findings and practical examples, scholars and practitioners tried to generate guidelines for effective SMM. Consensus exists that companies need to define an engagement strategy before diving into the SMM in order to appropriately approach the frequent users who are most likely to virally spread their enthusiasm for a new product or service (Li 2007a; Meadows-Klue 2008). These strategies should focus on (1) understanding the conversation, (2) establishing a relationship with the consumers, and (3) finding out which interactions, content, and features will keep users coming back (Kozinets et al. 2010; Li 2007a). These goals could be achieved by continuous and well defined measurement, fine-tuning and optimization of the undertaken actions (Meadows-Klue 2008).

Despite the recognized importance, evaluation of the proposed strategies is in a relatively early stage. This is partially due to the absence of clear objectives and goals which would define both, the measures to be used and the concept of effectiveness (Dubach Spiegler 2011; Murdough 2009), resulting in difficulties to link the social media activities to the organizational goals (Culnan et al. 2010). A general consensus exists that effectiveness evaluation of SMM should go beyond the traditional sales numbers by focusing on the engagement of the consumers on social media platforms (Hoffman and Fodor 2010; Murdough 2009). To confirm these assumptions, recently the focus of scholars turned to extending the existing marketing theories and applying empirical research on ways companies may foster customer engagement. For example, Jahn and Kunz (2012) argue that providing functional, hedonic and brand-interaction value to consumers could increase the engagement on Facebook brand pages, leading towards brand commitment, WOM, loyalty and, ultimately, purchase. In addition, an attempt to evaluate the effectiveness of SMM showed that a Facebook advertising campaign can increase the number of store visits and improve the brand attitude, resulting in greater emotional attachment and positive WOM

(Dholakia and Durham 2010). Still, as Wilson et al. (2012) point out, “these few studies only begin to touch on ways in which Facebook can be used to connect with customers.”

In order to set the stage for developing measures for the SMM effectiveness, Larson and Watson (2011) propose a social media ecosystem framework which distinguishes between the firm-initiated and customer-initiated actions and provides a theoretical understanding of what firms and customers accomplish through social media utilization. Based on the proposed framework, practical methods and measures were introduced (Krüger et al. 2012; Stieglitz and Dang-Xuan 2012). Yet these studies are focused on the SN Twitter and limit the analysis to the evaluation of the UGC.

To contribute in this direction, in this paper we propose an evaluation framework which allows companies to perform social media analytics through continuous monitoring of the content and activities on their social media marketing channels, and to measure the effectiveness of their marketing efforts on Facebook. The proposed framework extends the previous work by proposing analysis over three elements of SMM: (1) users, (2) UGC and (3) engagement, thus supporting the concept proposed by Larson and Watson (2011) which takes into the consideration the actions undertaken by both stakeholders, i.e. companies and consumers, yet expanding the evaluation beyond the UGC. Each component of the proposed framework is described in details, focusing on the (1) data source to be used, (2) method of analysis and implementation requirements for process automation, and (3) the relevance for SMM by pointing out to elements of the SMM strategies which are influenced by the obtained results and should be adjusted accordingly.

Before explaining the concept of the proposed framework, we will first provide an overview of the SMM in the context of Facebook in order to define the terminology. We will further use the Facebook terminology to provide detailed description of the methods involved in the evaluation framework.

3. Social Media Marketing on Facebook

The selection of Facebook as an underlying platform for this study was based on the reasoning that Facebook is currently the largest SN and the second most visited web page (Alexa 2012). In addition, Facebook is considered by the companies as the most attractive social media platform to be used for marketing purposes, in particular for B2C businesses (Hubspot 2012). This is further confirmed in a recent industry survey showing that 92% of companies are using Facebook for their marketing communication and 72% are planning to increase their activities on Facebook (Stelzner 2012).

In the context of Facebook, the platform provides four marketing possibilities:

- *Facebook Ads* appear on the right side of the Facebook page and they resemble any other online ad that is not specific to SNs. These advertisements are relatively passive - with indicators for success relying on measures such as number of (1) impressions, i.e. how often customers look at them, and (2) clicks, i.e. how often customers interacts with them.

- In contrast, *Facebook Brand Pages* offer the opportunity for a more active involvement, both on the side of the brand owner as well as the customer, who can become member of a company's Facebook page and - depending on the page setup – engage in a direct communication with the company.
- *Facebook Connect and Open Graph* protocols, allow Facebook members to log in to websites, mobile applications, etc., using their Facebook accounts, thus providing immediate access to their personal information and lists of friends.
- Finally, *Facebook Applications* provide access to a large number of users, serving the advertisement information in combination with the entertainment content.

Of these, we find the Facebook brand pages the most interesting since they provide direct access to vast amounts of UGC, revealing consumers' interests, needs and opinions.

3.1. Terminology Definition

In order to define the terminology, we will describe the concepts used in this paper based on the current definitions from Facebook (Facebook 2012c).

Although *like page* is the official name for all Facebook pages which are not profile pages, we will follow common practice and use the terminology *brand page* in order to distinguish pages operated by brand owners from those initiated by other users. The central part of the page displaying the UGC, i.e. the *posts*, is called the *wall*. Each page might have one or more administrators, i.e. the *moderators*, who can create or delete content on the page, and more important, set the *communication policy*, either allowing users to post on the wall, or restricting the user interaction to responding to the posts created by the administrator in a form of comments and likes. A brand page can have any number of members, in the continuation referred to as *users* or *fans*.

3.2. Available Data Sources on Facebook

The first step towards evaluation is data collection. There are two available sources of data describing the activities on a Facebook brand page: (1) *Facebook Insights* (Facebook 2012a), and (2) *Facebook Graph API* (Facebook Developers 2012).

3.2.1. Facebook Insights

Facebook Insights is a tool provided to administrators of Facebook brand pages to enable high-level monitoring of the activities on the page. It provides aggregated information on users, such as demographics (gender, age, language, etc.) and number of fans, as well as some details on the interaction on the page in terms of consumption and creation of the content. Data collected through the Facebook Insights tool allows analysis of the target audience characteristics.

While the demographics data is useful (and it can't be obtained from another source), the interaction data provided by the Facebook Insights tool might be inaccurate. For example, the number of post views is defined as a number of times people have viewed a story in the news feed, though this can only be counted as the number of times the post appeared on someone's profile wall and there is no guarantee that the post was seen or read. In addition, the features of Facebook Insights are controlled by Facebook. A change in policy could mean that a metric that was considered important by the company is no longer available. Finally, the Facebook dataset has shown gaps and errors visible in the Facebook Insights tool. Still, many of the shortcomings of the Facebook Insights tool can be worked around by using the Facebook Graph API described below.

3.2.2. Facebook Graph API

Facebook Graph API provides access to the interaction data via a uniform representation of the objects in the Facebook social graph (e.g., people, pages, etc.) and the connections between them. Upon a query, the data can be returned as a Page object containing connections such as Feed, Posts, Photos, etc. A *Feed* connection represents a list of all *Post* objects shared on the wall with the following relevant information: (1) post content, (2) post media type, (3) posting user, (4) likes, (5) comments, (6) application used for posting, (7) creation time and (8) time of last interaction. The interaction with the API is well documented at the dedicated page on the Facebook Developers site and will not be elaborated here further.

This rich data can be gathered for the wall postings of all brand pages, i.e. the company's own brand page, as well as competitor or related brand pages. In addition to this publicly available data, it should be noted that Facebook has recently offered the possibility to access the Insights data utilizing the Facebook Graph API, with administrator privileges. To companies with brand pages, this offers the possibility for automatic integration of the data from both sources for their own brand page. To guarantee the accuracy, we recommend the collection of the data to be performed on a daily basis, to ensure independence from potentially changing Facebook policies.

Based on the provided terminology, in the following section we describe the concept of evaluation framework for social media brand presence and provide detailed description of the methods for each of the framework components.

4. Evaluation Framework for Social Media Brand Presence

In this section we explain the concept and the methods of the evaluation framework for social media brand presence. We argue that a well defined evaluation framework is needed for utilizing SNs as a platform for SMM. As a support for our statement we use the following arguments:

- Due to the great diversity of different communities, there are no guidelines that could be set up in advance to guarantee the success in utilizing social media for marketing purposes (Coon 2010; Fidgeon 2011). This statement indicates that accepting existing solutions and guidelines which were found to yield success on some SMM platforms, does not necessarily lead towards the same positive outcome. Thus, individual and continuous evaluation is needed for each brand community.
- Implementing an evaluation phase with strategic control is a necessary component during the operational phase of a brand page (Dubach Spiegler 2011). This phase should be based on continuous analysis, on a level deeper than simple tracking of the number of fans and posts. In turn, obtained results could be used to adjust the company's SMM strategy, targeting the communication and posting policy, defining or altering the used metrics, or for larger strategic or organizational aspects of the management of a social media channel used for marketing purposes (Dubach Spiegler 2011).

To justify the selection of the framework components we summarize the findings and recommendations from the previous work in the field relevant for social media analytics and evaluation of the marketing efforts:

- Building an engagement plan as a part of the social media strategy should start by *focusing on the ongoing conversation* (Li 2007a). It should be taken in consideration that the communication on social media platforms is affected by the type of offered product or service. Therefore, the first step towards understanding the conversation should be classification of different types of content (Kozinets et al. 2010).
- The next step for creation of the engagement plan is *finding out which interactions, content, and features will keep users coming back* (De Vries et al. 2012; Li 2007a). In addition, previous findings showed that daily users exhibit significantly more interest in brand profiles (Li 2007b), and that triggering the user interaction could result in optimization of the marketing investment (Sterne 2010). Thus, understanding the effect of the actions undertaken by the moderators on SMM platforms should be included in the evaluation process.
- In the domain of Facebook as a platform for SMM there are still many open questions on how different companies could fit in with and adhere to the unwritten rules of engagement (Richter et al. 2011). As a result, companies are trying to define their social media strategies based on the insights from existing examples, but also based on their own trial-and-error experiences (Coon 2010). To avoid mistakes,

benchmarking to similar brand pages, competitors or best players could bring valuable insights.

- The final aspect to be investigated while performing the social media analytics derives from *the core element of SNs - the users*. The value of the evaluation of user characteristics over SMM channels has already been recognized (Fidgeon 2011; Li 2007b; Parent et al. 2011) as an important component for optimization of the social media utilization for marketing purposes.

Based on the presented reasoning we propose the following components of the evaluation framework:

- *User Analysis*. Who are the users and what are their characteristics? The answers to these questions contribute to the social media policy regarding the content and the tone of the conversation. Furthermore, since participation is the main element of SNs, categorization of the users according to their participation level and understanding the differences between the participation categories could help companies increase the overall level of engagement on their social media channels (Li 2007b; Parent et al. 2011).
- *User-Generated Content Analysis*. Listening to the conversation contributes in direction of understanding the topics that attract the attention of a large fraction of users, thus providing direct insights into the customer’s intentions, opinions, and perception of a given brand, product or feature. As such they support the objectives of market intelligence and product development (Richter et al. 2011). In addition, monitoring general trends enables brand image monitoring and buzz listening (Goorha and Ungar 2010; Kasper and Kett 2011; Stieglitz and Dang-Xuan 2012).
- *Engagement Analysis*. Analysis of the actions undertaken by the moderators on social media brand channels was already identified as an important step towards building an engagement plan which should reveal the actions that cause the greatest level of interaction (De Vries et al. 2012; Li 2007b). Obtained insights could help companies increase the level of engagement, which in turn could result in optimization of the marketing investment (Sterne 2010) by increasing the loyalty (Jahn and Kunz 2012), WOM communication (McAlexander et al. 2002) and brand awareness (Godes and Mayzlin 2004; Hoffman and Fodor 2010; Keller 2007).
- *Benchmarking*. Benchmarking against competitors was identified as a required step in both, the preparation and the evaluation of the company’s media presence. As such it plays an important role in the process of planning the company’s strategy for SMM (Dubach Spiegler 2011). In addition, in absence of proven strategies and guidelines, learning from existing practices provides the possibility to avoid errors, but also to define goals in terms of KPI values to be reached.

The full image of the proposed framework is presented on Fig. 1.

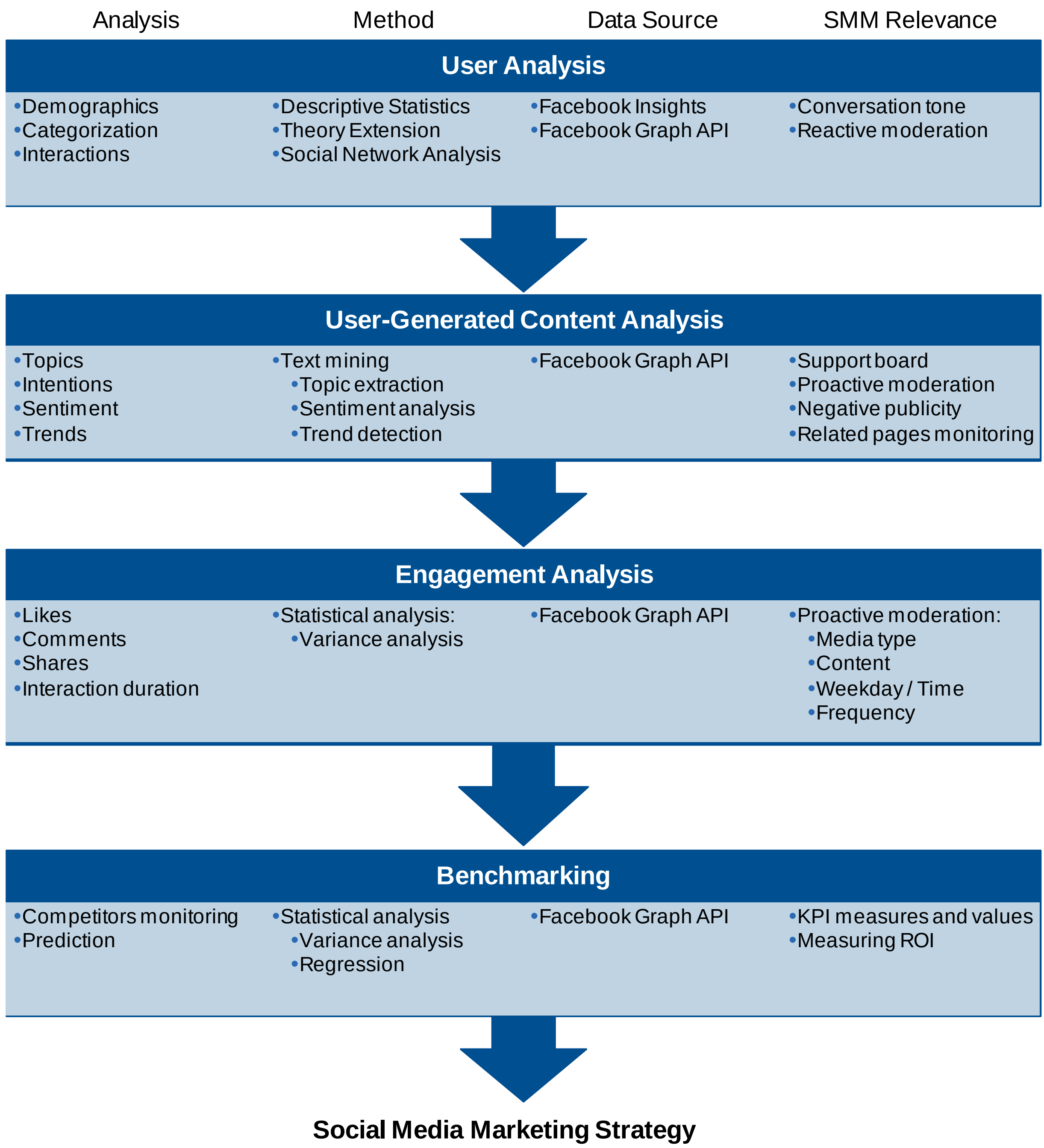

Fig. 1: Evaluation framework for social media brand presence.

In the continuation we will describe each component of the proposed framework, focusing on the (1) data source, (2) method of analysis, and (3) relevance for SMM, by pointing out to the elements of SMM strategies which are influenced by the obtained results.

4.1. User Analysis

Analysis of the users on Facebook brand pages should focus on three elements: (1) demographics of the users, (2) categorization, and (3) interactions between the users. Details of each step are provided in continuation.

4.1.1. Demographics

Analysis of the demographics data of the brand community members provides a possibility to gain general understanding of the target audience. Details of the proposed evaluation step are elaborated in continuation.

Data Source. Collecting demographics data on Facebook is one of the greatest challenges. Due to the existing privacy policies, only a limited amount of user details is available through the Graph API. In addition, demographics data provided through the Graph API is available only for the active fans, which can be identified from the undertaken actions, i.e. created post, comment or like. At the same time, demographics of inactive fans will remain unknown. Publicly available user data on Facebook contains: (1) name, (2) gender and (3) the language in which the Facebook page is displayed to the user, as a rough estimate of the native language.

In turn, Facebook Insights offers the demographics data in an aggregated format, allowing access to (1) gender and age distribution, (2) language, and (3) geographical distribution, i.e. cities and countries for the whole community. As such, Facebook Insights does not provide information regarding the specific characteristics of individual fans. Thus combining both sources would enable better understanding of the brand community by making a distinction between the demographics of the active fans and those that do not engage on the brand page, i.e. the lurkers.

Method. Analysis of the demographics data does not assume employment of a particular scientific method. Simple number monitoring, i.e. descriptive statistics, can provide insights into the target audience on a Facebook brand page.

A system that performs continuous monitoring of demographic data would provide the possibility for the companies to track the changes in the demographics and undertake appropriate actions. This functionality is already provided by Facebook Insights platform but only for the aggregated data. To integrate the data from both sources, an information system should be designed which would provide the following functionalities:

- Automatic import of the Facebook Insights data, into a designated database on a regular (daily) basis, and
- Collection and storage of demographic data provided through the Graph API for each active fan which engaged on the brand page by posting, commenting or liking.

Relevance for Social Media Marketing. Demographic numbers could be accepted by the company as a reflection of the brand's demographics. It should be taken in consideration that these numbers might be biased by the overall demographics distribution of the underlying platform. In turn, a more appropriate approach to these values would be to use them for adjustment of the conversation tone to the known participants on this communication medium.

4.1.2. User Categorization

As already mentioned, users have several options for interaction on brand pages: they might post content, comment or like an existing post. Based on this reasoning in the context of Facebook, users could be divided into the following categories:

- *Lurkers* - the category known in academic literature as inactive fans who participate in the community but do not undertake any action (Nonnecke and Preece 2000a),
- *Posters* - fans that contribute by creating posts on the wall of the brand page,
- *Commenters* - respond to existing posts with a comment, and
- *Likers* - indicate interest in an existing post by pressing the “Like” button.

The benefits of utilizing the proposed categorization for the companies are discussed in continuation.

Data Source. The data available from Graph API provides the possibility to identify different categories of active users and measure their contributions over time. This can be achieved by recording every undertaken action on the brand page by accessing the list of Posts created on the page. For the analysis performed in this evaluation step, of interest is the posting fan. In addition, to obtain a list of all Commenters and Likers, for each of the obtained Posts two additional sub-queries should be issued which provide access to the list of Comments and Likes made over the post.

Method. Categorization of the users is based on a theory extension. As such, the analysis which companies should perform to track the changes in the level of participation in each of the proposed categories is based on applying the principles of descriptive statistics.

A system that provides continuous monitoring of interaction data would provide the possibility for the companies to track the changes in the distribution of fans over categories and undertake appropriate actions. This can be achieved by implementing automatic collection of the content from the brand page as described above. Each of the obtained objects, i.e., posts, comments and likes, should be stored into database into separate tables to enable further distinction of the fans based on the undertaken action. A simple logic based on database queries should further be implemented to enable automatic categorization.

Relevance for Social Media Marketing. User categorization is of interest to the companies in order to understand how their customers use the social media platforms. Based on the obtained insights, appropriate strategies for proactive moderation could be developed (Dubach Spiegler 2011). This is in particular important since different interaction patterns result in different forms of UGC: while posting and sharing generate a story in the news feed of the user’s friends and on his profile page, thus supporting the goal of viral marketing by extending the reach of the marketing message, liking and commenting result in a trace which appears only as a short notification in the friends' ticker.

While the actions of the fans that interact with the page can be constantly monitored, activities of lurkers remain unknown. Even though lurkers make up the majority of the members, automatic measurement of their exposure to the brand is difficult since they take no action online; they might be reading every post, glancing at them occasionally or never see any of them, all without leaving measurable traces. This is one of the reasons why just measuring the raw number of users on a brand page is considered insufficient in understanding the online activities of the users. Still, findings show that daily users exhibit significantly more interest in brand profiles (Li 2007b). Therefore, improving the level of user's activity is a worthy goal that could be achieved by encouraging posters and preventing aggressive and mocking comments (Nonnecke and Preece 2000b).

In addition, the proposed approach provides the possibility to identify the "superfans". Companies need to devise a plan to address these fans directly, since these are the most enthusiastic members of the brand communities that initiate the marketing communication themselves, leading towards achievement of the WOM objectives (Harris and Rae 2009).

4.1.3. Interaction Analysis

Additional insights into the user activities could be obtained from the perspective of social network analysis (SNA). This approach would enable understanding of the brand community structure by shaping a network of interactions between the moderator and the users. In addition, interaction analysis provides knowledge about the brand community evolution over time and potential dependency from the community size.

Data Source. User categorization proposed in the previous section is based on the patterns of undertaken actions, i.e. posting, commenting and liking. Thus, to perform the interaction analysis, the same data should be used.

Method. The method proposed for this evaluation step is Dynamic SNA (DSNA) which provides the possibility for temporal visualization of the network structure and measures, i.e. visualization of the network evolution over time. To describe the characteristics of the interaction network, the following measures form the SNA theory (Wasserman and Faust 1994) should be applied:

- *Betweenness centrality*, as a measure of node's centrality, determined by the number of shortest paths between other nodes it belongs to, indicating node's importance to the network, and
- *Degree centrality* as a number of ties a node has, indicating the level of interaction the node has with other nodes from the network.

When applied to the network as a whole, these measures are commonly referred to as network centrality or centralization. Network centrality quantifies the tendency of a single point to be more central than other points in the network (Freeman 1979). As such, it is measured by the differences between the centrality values of the most central node and those of all other nodes, thus quantifying the variations among individual nodes. The closer the value is to 0, more uniform the users' behavior is. Finally, an additional measure used for characterization of the interaction network is:

- *Group density*, i.e. the proportion of existing ties between nodes relative to the maximal possible number of ties in the network. The higher density (closer to 1), indicates existence of larger number of ties, thus also a greater degree of interaction among the fans.

To create the interaction network, fans should be used as network nodes, while commenting and liking activities as network ties. Posting activity should not be taken in consideration since in the format provided by the Graph API all posts created by the users are addressed to the moderator, thus the resulting network has a perfect star shape and as such provides no insights.

Automation of the proposed methods would provide the possibility for real-time monitoring and timely reaction. This could be achieved by implementing a module for automatic data collection which should be integrated with an existing DSNA tool in order to enable interaction analysis on regular time intervals. A simple database query could extract the network structure and feed it to the DSNA tool.

Relevance for Social Media Marketing. The proposed analysis provides knowledge about the structural characteristics of the brand communities on Facebook, their evolution over time and dependency from the community size, i.e. the total number of fans. In addition, performed measures reveal:

- Importance of individual fans to the whole network,
- The level of interaction a fan has with other members of the brand community,
- Differences in interaction patterns between individual fans, and
- Degree of interaction between the members of the brand community and the moderator.

Obtained insights provide the possibility to identify the critical points in the network. In addition, it provides the possibility to identify influential fans, i.e. the network hubs. Both of these groups of fans should be encouraged to engage within the brand page since: (a) if a fan who represents a critical point in the network stops engaging, the network will lose its integrity by splitting into separate non-related sub-networks. In addition, (b) hubs are very influential fans which spread the content shared on brand pages to the largest audience, thus increasing the reach of the marketing message. Therefore, moderators should undertake reactive approach towards identified critical points and hubs to encourage their further engagement in the brand community. In addition, this approach also provides the opportunity for targeted marketing.

Existing theories from sociology suggest that there is a negative correlation between the level of interaction and the community size (Simmel and Wolff 1950). To address this issue, the proposed method provides an opportunity to identify the critical point in time when the interactions start to decline and undertake more proactive moderation in order to stimulate interactions and creation of social connections between the fans (Dubach Spiegler 2011).

4.2. User-Generated Content Analysis

In order to successfully run a Facebook brand page as a part of the SMM approach, marketing practitioners need to understand what people share and why. In this context, listening to the conversation should be considered as a two-step process: (1) analysis of the UGC from a company's brand page, and (2) analysis of the UGC contained in a form of Facebook public posts.

4.2.1. Content Analysis over Brand Pages

Analysis of the UGC from brand pages captures the following aspects of the posts created by page fans: (1) topics referred to within the posts, (2) intentions for participation, and (3) sentiment present in the content. Details of the proposed evaluation are elaborated in continuation.

Data Source. The data available from the Graph API provides the possibility to understand the content created by the fans on the brand pages. This can be achieved by collecting a list of Posts generated by the fans. For the analysis performed in this evaluation step, the content of the post is of interest.

Method. Research in the fields of opinion mining and sentiment analysis enables automatic identification and extraction of attitudes, opinions, and sentiments from the large amounts of UGC shared on social media platforms. Still, existing techniques are challenged by the text length limitation and lack of sentence structure or the use of informal Internet language common on social media platforms which differ from the formal written language that such analysis tools are optimized for (Yassine and Hajj 2010). To overcome these challenges, the action-object approach (Zhang and Jansen 2008) could be applied as a manual classification method, based on the Coding Development Strategy (Glaser and Strauss 1967). The process consists of three steps:

1. *Coding Strategy Development*: A manual coding scheme is created to define the classification rules, e.g. "brand -> mention of brand name"; "product -> mention of product name", etc.
2. *Tagging*: Using the defined coding strategy, each of the posts is assigned one or more tags to identify the key concepts in the content, e.g. "my favorite: ok.- chocolate bar, when will there be a jumbo pack?", would result in: 'product', 'positive affect', 'information inquiry', 'suggestion' and 'package'.
3. *Integrating*: Once the tags are assigned, grouping of similar tags is performed in order to identify group descriptors. For the previous example, the resulting descriptors are: (1) 'Product: Affect: Positive', (2) 'Sales: Availability: Launch Date: Information Inquiry' and (3) 'Product: Feature: Package: Suggestion'.

It should be noted that future optimization of the existing opinion mining techniques could significantly increase the effectiveness of UGC analysis by providing the possibility to replace the manual process with an automated one. One possible approach is to begin with manual analysis and then apply the tagged dataset as a training set to a learning algorithm. Thus an information system which would integrate the data collection process and algorithms for topic extraction and sentiment analysis would speed up the evaluation and avoid the need for employing additional personnel and time for manual content analysis.

Relevance for Social Media Marketing. The proposed method provides the possibility to the companies to understand their users by learning how and why they interact on the brand pages by approaching the task from two perspectives: (1) analyzing the topics referred to within the UGC and (2) revealing the intentions for participation. In addition, to address the fear of negative publicity on social media platforms, this method enables monitoring of the volume and valence of expressed sentiment, thus providing the possibility for timely reaction.

Apart from targeting the marketing objectives by revealing the answers to the questions such as perception of the brand, specific product or feature, acceptance of a new product, existing problems and perceived competitors, this analysis opens the opportunity for product development by focusing on the posts which contain ideas for new products or services.

Moreover, UGC analysis reveals the types of content which require a response by the page moderator. In addition, analysis of the topics of conversation is of organizational importance since it reveals which different sources of information should be available to moderators to successfully run a Facebook brand page. Since the nature of social media platforms implies immediate interaction, answers could be provided in timely manner by creating a support board behind the moderator, consisted of experts, which can be contacted when a specific question is posed. Continuous analysis should be used for adjustment of board members, since the initial knowledge in this field is still limited. This approach reduces the risk of undertaking an inappropriate action and exposing the company to possible fan loss.

Furthermore, since the topics and intentions for participation in brand communities are interconnected, the topic-category matrix can be used by practitioners as a tool that enables measurement of success of SMM utilization over time. Finally, sentiment analysis provides the possibility to avoid or minimize the negative publicity and fan loss by continuous monitoring and appropriate and timely response to negative content.

4.2.2. Content Analysis over Public Posts

Content analysis over public posts provides the possibility to the companies to track the conversation outside their own brand pages. Public posts are those posts which are being shared by Facebook users on their profile walls and can be obtained only if the user privacy policy is set to public. In addition, all posts shared on any brand page are publicly available.

The method described in continuation can be used to focus on the conversation on related pages, pages of known competitors, but also on the underlying platform as a whole in a form of trend monitoring which reveals the most popular topics.

Data Source. Collection of public posts available through the Facebook Graph API presents one of the challenges for content analysis on Facebook due to the existing privacy policies.

In addition, the Graph API does not provide the possibility to receive posts in the form of a real-time data stream. Instead, similar but limited functionality is available through the search feature, returning a list of public Posts for a given keyword. In order to collect all the public posts, a simple algorithm which performs a search, taking each ASCII character as a keyword, should be applied. The process should be repeated on regular and short intervals (15 minutes) to enable continuous data collection.

For the analysis performed in this evaluation step, of interest is the content contained within the created post.

Method. The method proposed for content analysis of large datasets such as those obtained from Facebook public posts is Term Frequency – Inverse Document Frequency (TF-IDF). TF-IDF is a weighting method for topic identification based on two measures: (1) the frequency of occurrence of a term within a single document, and (2) the number of documents in the corpus containing the given term (Jones 1972). Still, the original form of this method was found to be unsuitable for content shared on SNs due to the limited document length. To overcome this challenge, a concept of a hybrid document - containing all posts from the dataset - can be applied for the calculation of the TF component (Mathioudakis and Koudas 2010).

Once the weighted list is created, clustering of the terms that belong to the same topic can be done by:

1. Distribution – to eliminate the multiple occurrences of lexically similar n-grams with different lengths (originating from same posts), and
2. Co-occurrence – to group the terms that frequently appear in same posts, assuming that they refer to the same topic.

An information system which integrates both steps: continuous data collection and topic identification can be used for continuous trend monitoring. Depending on the preferences, this system could provide the possibility to distinguish between different data sources, e.g. competitors, related pages, or public posts shared on profile walls of Facebook users.

Relevance for Social Media Marketing. Detection and analysis of trends offer valuable insights into the topics that attract the attention of a large fraction of social media users as well as into the patterns of temporal distribution of different topics. These insights enable image monitoring, market intelligence and gathering ideas for non-brand related content communicated to the consumers on SMM channels. In addition, listening to the broader conversation provides the companies with the possibility to find out who the brand advocates are and approach them directly, but also to identify opportunities to revert dissatisfied customers.

The simplest form of monitoring of conversation on social media platforms, known as “buzz” monitoring is already considered as a good practice in the environment where the communication is not controlled by the companies, but is lead by the consumers themselves. Trend monitoring provides greater insights compared to buzz monitoring by finding the relations between commonly mentioned words by grouping them into topic groups.

Finally, tracking the conversation outside the brand page provides the possibility for more objective brand image monitoring which is not biased by the basic concept of brand page membership, i.e. “liking” the brand.

4.3. Engagement Analysis

Engagement analysis on brand pages should be performed in order to evaluate the effect of different actions undertaken by the page moderator over the level of consumer interaction. In the context of Facebook, there are two basic questions that correlate to the posting activity of the moderator: (1) what should a moderator post on the wall to trigger user engagement, and (2) when the content should be posted. The method to obtain the answers to these questions is described in continuation.

Data Source. The data available from Facebook Graph API provides the possibility to indentify the characteristics of the content shared by the page moderator on the brand page which result in highest level of user engagement. This can be achieved by collecting all Posts created by the page moderator, and looking into the number of actions undertaken by the fans over these posts.

Method. In order to answer the questions which content results in the highest level of engagement, the following two steps should be performed: (1) defining categorization rules for the posts by identifying the features that distinguish different posts, and (2) defining measures for user engagement over the posts created by the moderator.

In terms of categorization, posts created by the moderator can be distinguished by the (1) post media type, and (2) enclosed content. Post media type corresponds to the action undertaken by the page moderator. Facebook brand pages offer the possibility to create: (1) status posts (text only), (2) photos, (3) links, and (4) videos. Depending on the selected action, Facebook assigns the corresponding media type to each post.

A description of the content can be done through the topics reflected in the posts. Since the classification of the posts into topics might result in too many groups, thus making the further analysis difficult, we propose generalization of the topics in a form of a topic category representation, e.g. Advertisement, Information, etc. Classification of the posts into topic categories can be performed manually, since the moderators are creating the content with a particular goal in mind. Still, for expanding the analysis over additional brand pages, automation of the topic classification would reduce the complexity of the proposed method. A simple keyword based categorization algorithm could result in increased effectiveness of the proposed method.

In addition to the content, posting time is a factor that might influence the interaction level. Since brand posts appear, and are engaged upon, on the news feeds of the fans (Maurer and Wiegmann 2011), determining the optimal day and hour for posting, when the marketing message is most likely to be seen, could also result in increased engagement over the post.

Apart from allowing users to post, Facebook offers the possibility to comment or like the posts created on the wall. Based on this, the number of comments and likes can be used as an accurate measure for the level of engagement, as opposed to the number of daily active users and impressions provided by Facebook Insights. Further, it is important to note that the number of undertaken actions should be normalized with the number of page fans, in order to enable the possibility to compare the engagement level over longer period of time, and across brand pages which might have different community size. Finally, interaction duration can be used by page moderators as an indication for appropriate posting frequency.

In order to understand the differences in the engagement level caused by content with different characteristics, a statistical testing should be performed to quantify the level of difference in the obtained results and estimate its significance. The selection of the dependent and independent variables used for the statistical analysis should be based on the previously described reasoning: post characteristics represent the factors, while engagement measures are the outcome.

The selection of the statistical test for analysis of variance depends on the characteristics of the obtained data. Since the independent variables represent count variables, these will most likely have a Poisson distribution (Cameron and Trivedi 1998) which can be confirmed by normality testing. A Kruskal–Wallis non-parametric test for one-way analysis of variance is suitable for data which does not satisfy the normality condition.

Furthermore, to identify the sources of difference, the corresponding post-hoc analysis should be performed. For the Kruskal–Wallis test, an appropriate match would be the Mann-Whitney test with Holm's sequential Bonferroni correction (Holm 1979). Finally, the effect size, i.e. Pearson's correlation coefficient (r) can be calculated using the Z value from the Mann-Whitney tests (Field 2009).

Automation of the proposed method can be established by integrating the data collection algorithm with the algorithm capable of performing the statistical testing.

Relevance for Social Media Marketing. Customer engagement is the new key metrics for SMM (Haven and Vittal 2008) leading to the growing popularity of concepts such as Return-on-Interactions and Return-on-Engagement. The method proposed in this evaluation component enables measurement of the engagement level on Facebook brand pages over the content created by the company. Engagement measurement is performed on a level of individual posts, and is addressed through the number of undertaken actions, i.e. likes and comments, and interaction duration. Further, the method proposes four basic factors which influence the level of engagement over posts created by the moderators: (1) post media type, (2) content category, (3) posting day and (4) time. As such this method enables effectiveness evaluation of the actions undertaken by the company. The outcome of the proposed analysis, i.e. the list of content characteristic which result in highest level of consumer engagement, represents a direct input for planning of the posting strategy on Facebook brand pages.

4.4. Benchmarking

Since there are no established measures that would indicate a success when operating a Facebook brand page, an approach toward defining desired KPI values can be established by comparing the measured parameters with those obtained from similar brand pages. Apart from the known competitors, a company can gain additional insights by learning from the "best practice" examples on the underlying social media platform. Identification of the "best players" can be done by utilizing some of the existing platforms such as AllFacebook (2012), FanPageList (2012), etc., which provide ranking based on different criteria, such as the community size or engagement level. Based on the obtained data, a model can be derived which would enable prediction of the outcome of the undertaken actions. The details of the proposed approach are elaborated in continuation.

Data Source. Facebook Graph API provides the possibility for the companies to access the full interaction data of any Facebook page, thus enabling the opportunity to perform same analysis as those already described in the previous components of the proposed framework. The only information that is not fully available for benchmarking is the aggregated demographics data which is available only to the page moderators through the Facebook Insights platform.

Depending on the company's characteristics and interests, filtering criteria for similar brand pages may be applied, including, but not limited to: (1) brand characteristics, (2) product or service type, (3) region, (4) nationality, (5) target group, (6) communication policy, (7) community size, or (8) moderation style.

Method. Benchmarking implies comparison of the results obtained from company's brand page to those obtained from other brand pages. As such, benchmarking can be achieved by performing the same analysis already described in previous sections over a larger dataset. Thus no further description of these methods will be presented in this section.

In addition to the methods included in the previous three components of the evaluation framework, integration of the existing marketing theories and their empirical evaluation over large dataset provides the possibility for creation of structural models which can be used to clarify the relations between the traditional marketing constructs. Structural equation modeling (SEM) allows for both, confirmatory and exploratory research. As such, this approach is suitable for the field of SMM where many questions still exist, mostly due to the differences in the marketing communication compared to traditional one-to-many promotion. The created model can further be used by the companies for prediction of the values of the relevant metrics based on the undertaken actions.

An information system capable of (1) collection of the data from multiple brand pages based on the predefined criteria, and (2) (semi)automatic structural model improvement based on the empirical evaluation and manual configuration, could provide the possibility for process automation resulting in an efficient generation of guidelines in a form of KPI values to be reached and strategies to be emulated.

Relevance for Social Media Marketing. Benchmarking against competitors and other brand pages has direct influence over the selection of the elements of the communication strategies on social media platforms used for marketing purposes. Comparison across multiple brand pages could provide insights such as:

- What is the average community growth rate across the brand pages?
- How large is the proportion of active fans (posters, commenters and likers)?

- How large is the proportion of returning fans, i.e. those that posted more than once?
- Which posting frequency results in the highest level of engagement?
- Which is the optimal posting time yielding towards higher engagement level?
- Which topics are commonly reflected in both, posts from the fans and the moderators?
- Which content triggers the highest level of engagement?
- Which mode of engagement is most commonly used by the fans?
- What is the average number of posts created by the fans over the selected time interval?
- What is the most commonly used moderation style?
- What is the most commonly practiced communication policy?
- Which sentiment is mostly expressed by the fans and how big is the risk of a negative publicity?
- …

This data can serve as the basis for further investigation and a source for gathering knowledge by analyzing moderation methods from similar and related brands.

Moreover, the measures referred to within the above listed questions can be used as KPIs and their reference values to be achieved can be obtained by answering the above questions through analysis of the “best players” on the underlying platform. Finally, the proposed analysis could even be expanded to other Facebook page categories, for example fan pages created by celebrities, which also show remarkable results measured by the number of fans.

Statistical analysis of the obtained numbers could provide insights into the influencing factors that increase the SMM effectiveness in terms of engagement, loyalty, WOM communication and community growth. In addition, derived statistical models can enable prediction of the changes and development of the relevant metrics for SMM, such as the number of fans. Thus, the results obtained from the large scale analysis of the data, provides the possibility to prepare initial communication and posting strategies. In addition, continuous and real-time monitoring of the obtained results enables tracking of the potential changes in the community and their responses to the undertaken actions, and creates an opportunity for the companies to undertake appropriate steps to adjust the initial strategies in accordance to the specific characteristics of their brand communities.

5. Proof of Concept: Results of the Evaluation of the ok.- Brand Page

To provide evaluation for the approach proposed above, we introduce the case study of the ok.- Facebook brand page, illustrated on Fig. 2.

Fig. 2: The ok.- Facebook brand page with sample postings by the moderator.

The private-label brand ok.- was created by the Swiss company Valora in 2009 as “good and affordable” brand offering “useful products and services which make everyday life more enjoyable” (ok.- 2012). The advertising slogan "... is totally ok.-" soon reached the younger consumers which became apparent on the company’s Facebook Page. At the time of writing the page counts 276,944 members with an ongoing and active discussion of the wall.

In addition to the available data from Facebook Insights, data collection based on the Graph API was employed from July 2010 to March 2011, and the data from the official launch of the brand page in March 2010 to July 2010 was fetched retroactively to ensure a complete data set. Over this time, 134 moderator posts were gathered (average of 0.33 posts per day). In addition, users shared 625 posts, thus making a total of 759 posts.

5.1. User Analysis

The combination of the demographics data from the Facebook Insights and the interaction data collected by utilizing the Facebook Graph API provided insights into the characteristics of the users on the ok.- brand page. In the continuation, we present and discuss the results obtained by applying the described approach (Pletikosa Cvijikj and Michahelles 2012).

5.1.1. Demographics

User demographics were initially of key interest to the moderator team and the brand owner. Repeated inspection showed a clear and consistent base of young users, resulting with 68% of the total fans at the end of the observed period having between 13 and 17 years. The next biggest block consisted of 18 to 24 year-olds (25%). In terms of gender distribution, the groups were almost even, 48% of the fans were male and 52% female. These demographic numbers were quickly accepted by the company as a true reflection of the brand's demographics, which in turn validated the use of Facebook as an appropriate medium for communicating with the target consumers for the ok.- brand. Fig. 3 illustrates the previously presented numbers.

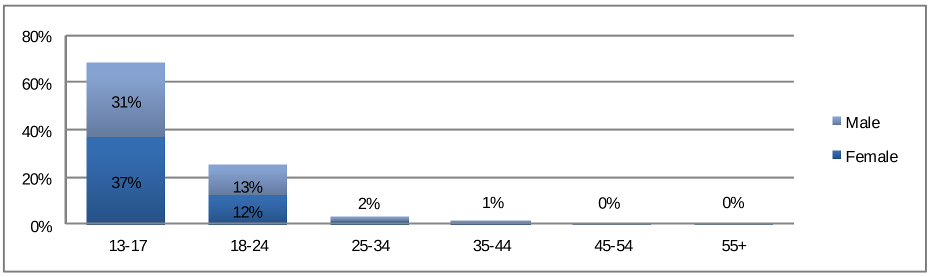

Fig. 3: Demographics of the ok.- Facebook brand page reflects the target group for the ok.- brand.

5.1.2. User Categorization

Measured by absolute numbers, the number of active users increased during the selected period, from 28 in March 2010, to 853 in February 2011. However, percentagewise the situation was the opposite. With the growth of the total number of fans, the percentage of active fans was reduced, from 8% to 2% of total number of fans.

Furthermore, the level of activity measured in terms of fans distribution over classes of active users was also reduced. From initial 82% of posters, in relation to the number of active fans, this class was reduced to 48% at the end of the study. In turn, the percentage of commenters and likers slightly increased. From initial 0%, at the end of the study the commenters have reached the number of 26% of the active users, while the percentage of likers did not show large variations, ranging between 18% and 28% of the active users. Fig. 4 illustrates the distribution of fans over different categories.

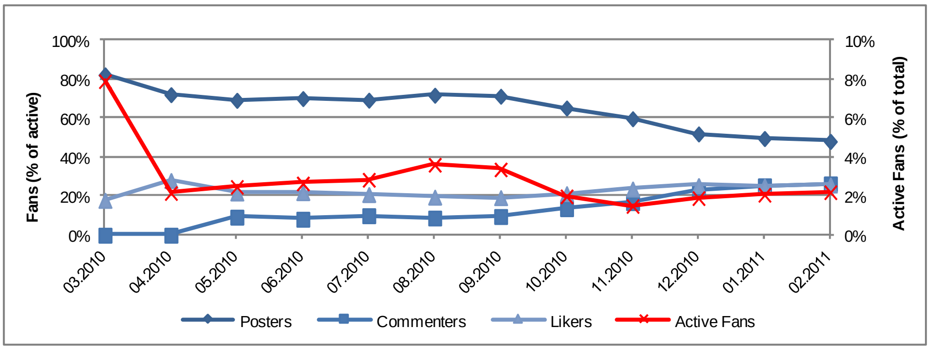

Fig. 4: Development of the number of active fans as a proportion of total number of fans (right axis) and individual classes of fans as a proportion of active fans (left axis).

The observed decrease in the interaction level complies with the existing research from sociology which indicates that an increase in the size of the social network has negative effect over the interactions between individuals (Simmel and Wolff 1950).

For visualization, lurkers were intentionally left out in this picture since on the ok.- brand page they represented 98% of the fans at the end of the observation period, which is high compared to the 90% predicted (Nonnecke and Preece 2000a).

5.1.3. Interaction Analysis

To observe if the similar effect of the community size exists over the structural characteristics of the interaction network, we have applied DSNA over the selected period. Furthermore, we have divided liking and commenting activities into separate networks to see if they show different evolution over time. The results of the analysis performed over the commenting network are illustrated on Fig. 5.

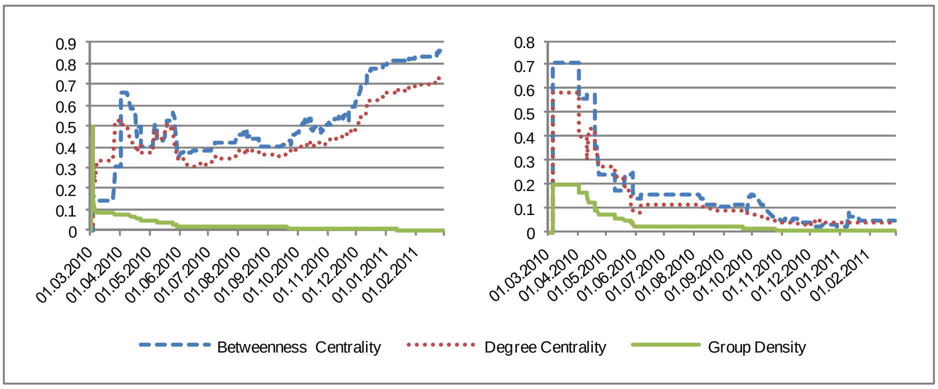

Fig. 5: Betweenness, degree centrality and group density of the commenting network: (a) with the moderator (left), (b) without the moderator (right).

Fig. 5a shows that the group density exhibits initial peak in March 2010, then falls down and continues into a relatively stable phase. In contrast, both centrality measures show increases over time indicating that some fans are more active than others. Since this network includes both, fans and the moderator, we have assumed that the obtained results are biased by the moderator. For that reason, we have filtered out the comments from and to the moderator, resulting in a network structure shown on Fig. 5b. It becomes clear that without the moderator, commenting interaction between the users decreases over time.

In terms of liking, the characteristics of the interaction network are illustrated on Figure 6.

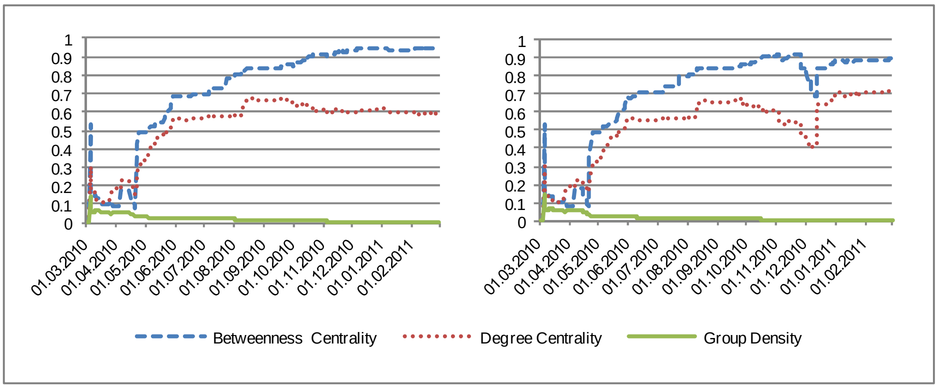

Fig. 6: Betweenness, degree centrality and group density of the liking network: (a) with the moderator (left), (b) without the moderator (right).

While there is a difference in the shape of the applied measures, on overall level results presented on Fig. 6a resemble those shows on Fig. 5a. Still, when the moderator is removed from the network the behavior of users resembles the behavior of the network in whole as illustrated on Fig. 6b. This means that while some fans frequently like the content shared by other fans, others only occasionally or never engage. This finding can be used as an indication that fans feel free to express themselves by performing the action of “liking” which does not expose them to possible follow-up reactions by other users.

The presented results indicate that a company should undertake more active moderation with the increase of the size of the community in order to encourage creation of relations between the fans. This might be achieved by organizing activities such as competitions, polls, discussions, etc.

5.2. User-Generated Content Analysis

5.2.1. Content Analysis over Brand Pages

As a confirmation for the validity of the method proposed in the previous section, we present and discuss the results obtained by applying the described approach over the content shared by the fans on the ok.- brand page (Pletikosa Cvijikj and Michahelles 2011a).

Post Topics. The initial goal of the study was to understand what fans talk about on a Facebook brand page, i.e. to identify the topics of conversation. As a result, seven major topic groups were identified: (1) Product, (2) Sales, (3) Brand, (4) Competitor, (5) Facebook Contest, (6) Company and (7) Environment. An additional benefit of the proposed approach is the possibility to understand the content with a better granularity by dividing each topic group into more specific sub-topics as presented on Fig. 7.

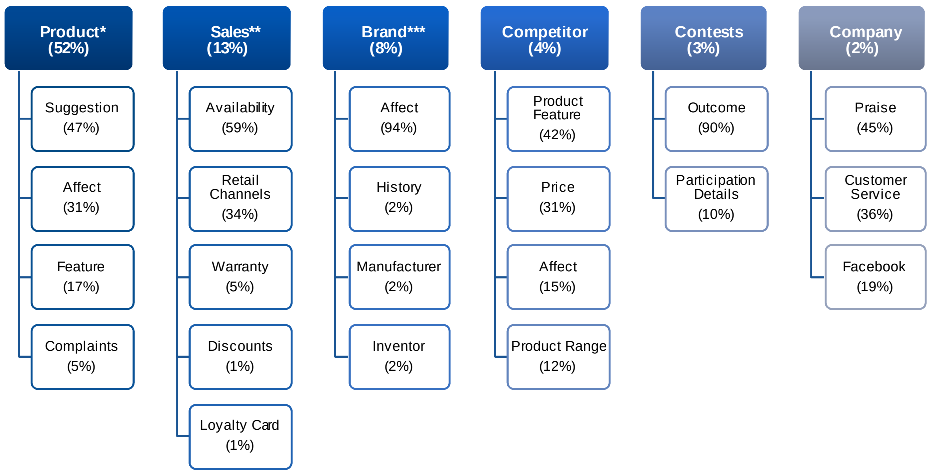

Fig. 7: Posts of the ok.- Facebook brand page analyzed for semantic content revealed seven major topics, further subdivided into subtopics (*$p < 0.0001$, **$p < 0.005$, ***$p < 0.05$). Distribution values of sub-topics is relative to the topic group.

For the page moderators, this analysis provided proof that the content of the ok.- Facebook brand page fulfilled the expectations by having the top three categories be Product, Sales and Brand. This has confirmed that consumers use the brand page for brand-related conversations, which in turn reveals (1) perception of the brand, (2) acceptance of new product, (3) most favored products and features, (4) potential problems, (5) locations with great volume of sales, and also may serve to (7) generate ideas about new products and services.

Organizationally, the topics can be used to understand which different sources of information need to be available to moderators to support them in providing a timely response to the page fans. The presented results indicate the need for following members of the moderator support board: (1) sales, (2) logistics, (3) company/brand information, (4) product information and (5) environmental issues.

Intentions for Participation. A reverse reading of the initially assigned group descriptors resulted into the discovery of the following intentions for participation: Suggestions & Requests (170 posts or 27% of the total), Affect Expression - for a product or the brand (169, 27%), Sharing – e.g. advice, information, need (165, 27%), and Information Inquiry (98, 16%). In addition, Complaints & Criticism (23, 4%) were treated as a special form of Affect

Expression which requires an action from the moderator in order to avoid negative publicity. Similarly, Gratitude (22, 4%) and Praise (5, 1%), were also separated since the expressed sentiment was not targeted towards a product or the brand. Fig. 8 provides better visualization of this data.

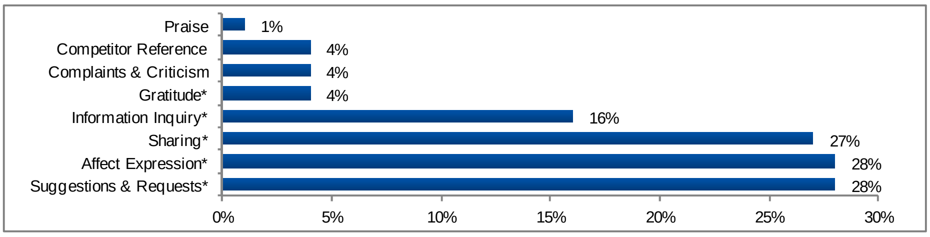

Fig. 8: Posts of the ok.- Facebook brand page analyzed for semantic content revealed eight major intentions for participation (*p < 0.0001).

In contrast to the topics, intentions on their own were not as meaningful to the moderators or as useful in understanding the users. The exceptions were the Information Inquiry and Complaints & Criticism, which require moderator action. Thus, this number can be used in resource planning.

Topic-Category Matrix. Since topics (i.e. objects) and categories (i.e. actions) are interconnected, a matrix can be drawn up to identify dominant pairs, as illustrated in Table 1.

	Product	Sales	Brand	Competitor	Contests	Company	Environment	General
Requests & Suggestions	24%	3%	-	-	-	-	0%	-
Expressing Affect	20%	-	7%	0%	-	-	-	-
Sharing	-	-	-	-	-	-	-	27%
Information Inquiry	5%	8%	0%	-	2%	0%	-	0%
Complaints & Criticism	3%	0%	-	-	-	0%	0%	-
Expressing Gratitude	0%	1%	-	-	2%	0%	-	0%
Praise	-	-	-	-	-	1%	-	-

	Product	Sales	Brand	Competitor	Contests	Company	Environment	General
Comparison	-	-	-	4%	-	-	-	-

Table 1: Combination of post topic and category pairs. Of interest are both the empty spaces which might indicate potential for development, as well as the dominant pairs which indicate the highest need for moderation.

Apart from Sharing (27%), Product Requests and Suggestion (24%) and Expressing Affect towards the Products (20%) were found to be the most dominant topic-category combinations. Overall, these numbers confirmed that Facebook can be used as a suitable platform for SMM, since the dominant intentions, topics and their pairings were all in line with the company's expectations for building brand awareness, gathering insights and knowledge for future steps, community involvement and engaging in dialog.

Sentiment Analysis. A final view on the existing data was an analysis conducted to determine how users feel about the brand or the products. This understanding was gained by categorizing the sentiments shared within the posts from the Affect Expression category identified above. The results showed that positive sentiment was shared far more often (25% of the total posts) compared to negative (2%). Marketing practitioners can use the sentiment analysis and topic-category frequency as a measure for successful SMM utilization over time.

5.2.2. Content Analysis over Public Posts

Evaluation for the proposed approach for automatic trend monitoring over Facebook public posts will be given by summarizing the results of a study based on the described method (Pletikosa Cvijikj and Michahelles 2011c).

The evaluation of the proposed algorithm was based on the common approach of measuring the precision and recall (Raghavan et al. 1989). The results of 10 experiments have shown the following average values: Precision = 0.7139, Recall = 0.5771 and F-measure = 0.4773. These values indicate that on overall level the proposed algorithm performs well.

Although the presented results apply for global trend monitoring, the same approach can be applied by the companies to monitor the conversation related to specific topic, brand or product. The results of such analysis would reveal the most significant sub-topics that are commonly related to the company's topic of interest, i.e. product, brand or industry branch on a more global level.

In addition, the analysis of the identified trending topics, revealed the possibility to distinguish among three different categories of trends: (1) disruptive events, (2) popular topics and (3) daily routines. These topics can be used to engage the users in a non-brand related communication on SMM channels. Finally, obtained results showed that topics which attract a lot of attention on traditional media do not necessarily become trending topics on social media platforms, providing the possibility to select the content suitable for the underlying media platform.

5.3. Engagement Analysis

The results presented in this section were obtained by analyzing the effect of the moderator posts on the ok.- brand page (Pletikosa Cvijikj and Michahelles 2011b).

Post Categorization. For the presented case study, the assignment of the categories to each of the posts was done manually by the company's social media manager. The assigned categories were: (1) Product Announcement, (2) Information, (3) Designed Question, (4) Questioner, (5) Competition, (6) Advertisement and (7) Statement. These are described in details in the previously referenced paper.

In the continuation we describe the obtained results of the statistical analysis.

Post Type. In the used dataset only three post types were present: status, photo and link. The statistical analysis has shown that there is a significant effect of post type on all three variables, the likes ratio ($H(2) = 20.24$, $p < 0.0001$), the comments ratio ($H(2) = 21.90$, $p < 0.0001$) and the interaction duration ($H(2) = 11.32$, $p = 0.0035$). As visible on Fig. 9, photos have caused the greatest level of interaction, followed by statues and links.

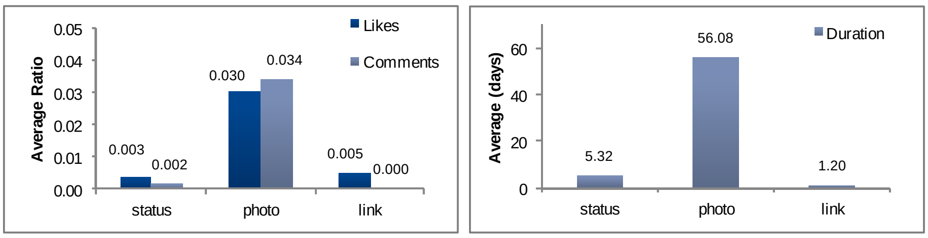

Fig. 9: Two measures of user interaction: (a) mean values of likes and comments in response to the three post types (left) and (b) mean values of interaction duration in days (right).

Post Category. Significant effect of post category was also found to exist on all three variables, the likes ratio ($H(6) = 34.34$, $p < 0.0001$), comments ratio ($H(6) = 35.54$, $p < 0.0001$) and the interaction duration ($H(6) = 17.28$, $p = 0.008$). Fig. 10 illustrates that Advertisements and Announcements have caused the greatest level of interaction, confirming the results of the content analysis, i.e. brand page fans are interested in receiving information regarding the brand and products.

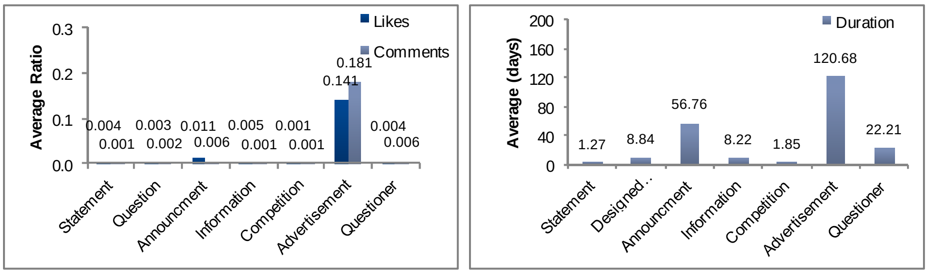

Fig. 10: Mean values of (a) likes and comments in response to the post categories (left) and (b) interaction duration in days (right).

Posting Weekday. In terms of the effect of the posting weekday over the level of user interaction no significant effect was found to exist (p > 0.05). An effect only occurs over the comments ratio (H(6) = 14.00, p = 0.030). In addition, the significant difference in the comments ratio exists only between posts shared on Tuesday and Thursday (p = 0.019, r = 0.54). Still, looking at the mean values of engagement measures reveals certain differences, as illustrated on Fig. 11. This indicates that further examination is needed.

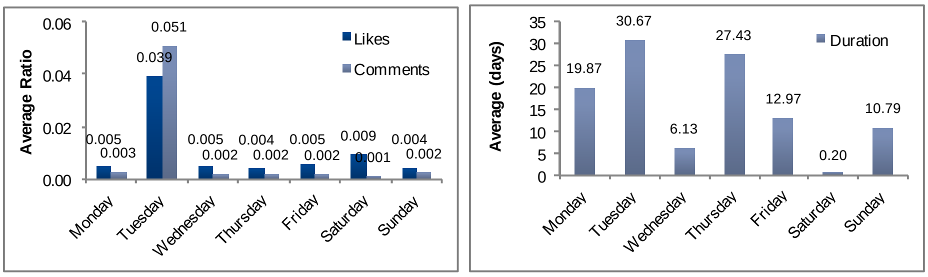

Fig. 11: Mean values of (a) likes and comments in response to the posting day (left) and (b) interaction duration in days (right).

Posting Hour. Similar to the posting day, the effect of the posting hour over the level of user interaction was not found to exist (p > 0.05). Yet again differences appear in the mean values of engagement measures as visible on Fig. 12. These results suggest that posts created in the morning and evening could increase the number of likes and comments, while those created in the morning and early afternoon result in longer interaction. Still, further examination is needed to confirm these assumptions.

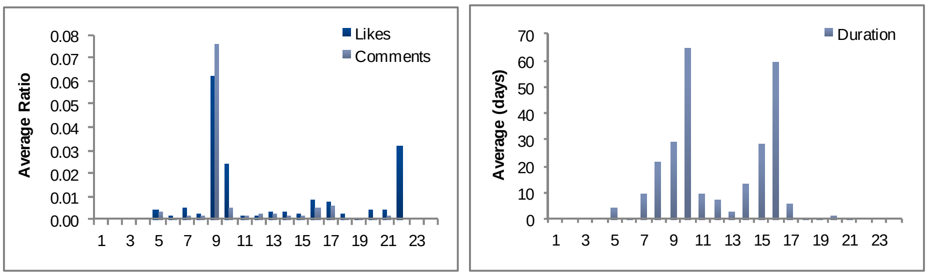

Fig. 12: Mean values of (a) likes and comments in response to the posting hour (left) and (b) interaction duration in days (right).

The presented results show that different media types and content categories cause different interaction levels and this information provides a basis for planning of the communication strategy. Furthermore, the effect over comments and likes ratios is larger compared to the effect over the interaction duration. This is related to the fact that the Facebook wall can only display a limited number of posts. Once the post is not visible the probability for interaction reduces or ends. The length of the interaction over photos is significantly longer due to the fact that all photos were posted in same album. Once the album is open, the probability of interaction with older photos increases.

In turn posting day and time were not found to be influential factors for the engagement. It should be noted that these results might be due to the fact that non-parametric statistical tests are less powerful. We plan to investigate this further in future studies.

5.4. Benchmarking

In order to compare the performance of the ok.- brand page to national and international competitors, data from an additional 14 brand pages was collected over the course of four months, from February 2011 to June 2011. This resulted in an additional 131,114 posts, of those 1,494 from the page moderators. The selection criteria for these pages were: (1) region (Switzerland), brand (private label and low-cost brands), category (fast-moving consumer goods) and the top-seller items (energy drinks). Table 2 illustrates the high-level characteristics of the selected brand pages.

Brand	Fans				Mod. Posts		Fan Posts	
	N[a]	Growth[b]	Posters[b]	Returning[d]	N[b]	AVG[c]	N[b]	AVG[c]
Coca-Cola	28,966,208	31%	0.76‰	9%	50	0.42	26,548	221.23
Disney	24,702,363	49%	0.01‰	5%	71	0.59	418	3.48

Brand	Fans				Mod. Posts		Fan Posts	
	N[a]	Growth[b]	Posters[b]	Returning[d]	N[b]	AVG[c]	N[b]	AVG[c]
Starbucks	22,608,089	16%	1.09‰	12%	74	0.62	28,842	240.35
Oreo	20,405,952	23%	0.45‰	5%	59	0.49	9,635	80.29
RedBull	19,637,223	31%	0.01‰	2%	96	0.80	132	1.10
Pringles	14,245,112	60%	0.28‰	5%	20	0.17	4,495	37.45
Monster Energy	10,921,349	32%	1.21‰	14%	258	2.15	17,411	145.09
Nutella	10,351,315	38%	0.03‰	3%	15	0.13	410	3.41
Dr Pepper	9,409,769	22%	1.52‰	10%	265	2.21	17,018	141.81
WalMart	6,212,914	107%	1.85‰	11%	192	1.60	13,616	113.46
Target	4,597,023	13%	1.05‰	10%	67	0.56	5,767	48.05
Walgreens	1,070,345	26%	2.05‰	14%	111	0.93	3,437	28.64
Kmart	425,625	32%	2.87‰	14%	210	1.75	1,576	13.13
M-Budget	25,344	2%	8.28‰	14%	6	0.05	315	2.62

[a] Obtained on June 1st, 2011
[b] For the selected period
[c] Daily average value
[d] Relative to the posters

Table 2: List of Facebook brand pages chosen as a basis against which to compare the performance of the ok.- Facebook brand page.

These numbers were initially collected to validate the previously presented results of the moderator analysis for the ok.- brand page (Pletikosa Cvijikj et al. 2011). Similarly, only the effect of the post type and category was confirmed. However, the process of post categorization revealed large differences in the moderator posts in terms of referred topics. While the ok.- page, as an emerging brand, was mostly focused on providing product related information and encouraging the interaction through designed questions, other pages did not follow the same pattern of communication. Well established brands, such as Coca-Cola or Red Bull were posting content related to the timely relevant events, such as sports events or the Royal Wedding. This had influence over the results of the post-hoc analysis which differed from those obtained from the ok.- page in terms of sources of significant difference. These findings provide a confirmation of the requirement for the companies to perform continuous analysis and measurements of the activities on their brand pages since no unique guidelines can be applied to the specific characteristics of different brand page communities.

Apart from the formal evaluation, previously presented numbers were also used by the moderator team to gain a general understanding of the brand pages and possible comparison measures. Some sample insights were:

- The range of number of fans varies greatly, revealing that this is not an appropriate measure for comparison unless careful selection of brand pages has been done, e.g. ok.- brand is a regional brand, while Coca-Cola is international brand. More appropriate measure could be the normalized value, i.e. the fans growth rate.
- In terms of user categories, it can be seen that in all cases the number of posters is far below 10% as reported in previous studies. Interesting observation is that the larger the total number of fans, the smaller the group of posters becomes. This pattern was also observed on the ok.- page by tracking the user categories distribution over time as illustrated on Fig. 4.
- As a measure of loyalty, the number of returning posters can be used. In most cases similar pattern can be seen as with the number of posters. These relations should further be investigated.

The ongoing nature of the moderation tasks that a Facebook brand page brings with it, and the related learning that occurs over time, are the main features of successfully moderating a Facebook brand page.

6. Summary and Conclusions

Formulating objectives and providing information systems to measure the relevant metrics is necessary for controlling the marketing efforts on social media platforms. To address this issue, we have proposed an evaluation framework which enables companies to perform social media analytics, through continuous monitoring of the content and activities on their SMM channels, and to measure the effectiveness of their marketing efforts on Facebook. The proposed framework is consisted of four components: (1) User Analysis, (2) UGC Analysis, (3) Engagement Analysis, and (4) Benchmarking. A detailed description of each component was provided, revealing the (1) data source to be used, (2) method of analysis and implementation requirements for process automation, and (3) the relevance for SMM, by pointing out to the elements of SMM strategies which are influenced by the obtained results and should be adjusted accordingly. Continuous utilization of the proposed framework could enable early problem detection and reaction from the companies in form of strategy adaptation in accordance with the specific characteristics of their brand communities. Thus the main objective of the proposed approach is to support the process of social media monitoring and adaptive management of companies' SMM efforts, i.e. fine-tuning of the initially established SMM strategies based on the obtained results.

In order to illustrate the practical application of the proposed methods, we presented the results obtained from a case study of a Facebook brand page. We discussed the value these results bring for marketing practitioners from the perspective of planning the SMM strategies:

- Users' characteristics provide the possibility to categorize and measure the level of user's activities. Improvement of the existing activity level could be achieved by encouraging posters and preventing aggressive and mocking comments (Nonnecke and Preece 2000b). In addition, by understanding the nature of the "superfans", an opportunity for targeted marketing appears. Finally, demographics can be used as an indication of the brand's demographics, but also to adjust the tone of the conversation to the known participants on this communication medium.
- Content analysis of the posts shared by users shows clearly what types of questions and comments require responses from the moderator. In addition, it indicates a need for "board of experts" to enable prompt answers to the users as expected on SN platforms. Continuous analysis can be used to fine-tune the assignment of experts which will reduce the impact of missing initial preparations, by learning the true requirements as needed. Finally, by listening to the conversation, a company could gather ideas for new products and services which are perceived as needed by users themselves.
- Moderator Analysis shows clear evidence that it is possible to increase the level of interaction by carefully planning the posting strategy. Apart from revealing the media types and content categories of posts that attract the majority of the users, it provides the possibility to plan the posting frequency based on the estimated interaction duration.
- Benchmarking provides an alternative view on a brand's efforts with SMM by monitoring the competition or leading brand sites. For this, gathering data from related brand pages can provide valuable data against which to benchmark the brand's efforts, and they can be used to identify successful brand pages whose moderating style or practices can be emulated.

This paper demonstrated that by following a structured process a company's brand page can be systematically evaluated. Setting measurement criteria, gathering data and analysis at set intervals will allow a company to monitor and improve their SMM efforts. The paper's academic contribution consists of presenting a new evaluation framework for social media brand presence and a detailed discussion on the related analysis methods and insights for the companies gained through their utilization.

7. Limitations and Future Work

The framework and results presented in this paper are subject to two main limitations which in turn open opportunities for future research. First, the concepts presented in this paper are limited to the selection of Facebook as a platform for social media marketing, and second, the evaluation of the proposed framework is based on a single case study from the Fast-Moving Consumer Goods (FMCG) domain.

The selection of Facebook as underlying platform was based on the fact that Facebook is currently the largest social media platform, and as such it is considered as the most appealing SMM platform by practitioners. Though the used terminology reflects this choice of social media platform, it is important to note, that the concepts such as brand community, fans, i.e. brand community members, social connections and interactions, moderation and engagement, are basic to any SN. Thus the proposed framework is generic enough to be translated to other existing or future SN platforms, such as Twitter, Google+, etc. The main difference to be considered is the data collection process, which will differ for different social media platforms. Thus, building a system that has a modular architecture, such that additional modules for data collection can be added, is the next step to be undertaken.

Moreover, the concepts presented in this paper represent a snapshot corresponding to the currently available marketing and engagement possibilities on Facebook. Future changes might result in additional engagement possibilities, content types, etc. These might also influence the dialog lead between the companies and consumers on Facebook brand pages, thus posing new questions to be addressed. In addition, differences in the engagement possibilities and content characteristics could also appear between different social media platforms. Thus to enable automatic and continuous evaluation, the proposed system should also provide the possibility to select and configure the available engagement modes and specific content characteristics relevant for the selected social media platform.

The selection of a case study approach for evaluation was based on the possibility to establish collaboration with an industry partner which provided: (1) insights into the challenges and questions faced upon practitioners when trying to integrate social media into their marketing communication, and (2) access to the complete usage data of their Facebook brand page, i.e. data available through the Facebook Insights platform. In order to generalize the obtained results and investigate the potential differences across different industry domains, similar studies need to be conducted over larger number of brand pages, which correspond to different product or service types.

It should be noted that the proposed framework involves certain computational and organizational complexities. The computational complexity, addressed from the perspective of required resources, i.e. time and space complexity, is assumed to be linear, based on the preliminary findings. Still, as already discussed in Chapter 4, certain steps which are conducted through manual analysis should be further refined and replaced with automated processes which would significantly simplify the practical application of the proposed methods. This in particular applies to the content classification, where evaluation of the existing text mining techniques should be performed in order to select those which yield satisfactory results. Once this goal is achieved, a formal evaluation of the computational complexity can be conducted to confirm the initial assumptions. In addition, practical application of the proposed framework would allow for estimation of the organizational complexity, in particular for integration of the proposed framework in the company's structure and processes.

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