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Evaluation Framework for Social Media Brand Presence

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IRENA PLETIKOSA CVIJIKJ

MSc in Electrical Engineering, Ss Cyril and Methodius University, Skopje, Macedonia

born June 7, 1976

citizen of Macedonia and Croatia

accepted on the recommendation of

Prof. Dr. Elgar Fleisch
Prof. Dr. Katarina Stanoevska-Slabeva
Dr. Florian Michahelles

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Dedicated to my family.

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ABBREVIATIONS

API	Application Programming Interface
CR	Comments Ratio
CTR	Click-Through Rate
DSNA	Dynamic Social Network Analysis
ER	Engagement Rate
ETD	Emerging Trend Detection
eWOM	Electronic Word-of-Mouth
FMCG	Fast-Moving Consumer Goods
HCI	Human-Computer Interaction
JSON	JavaScript Object Notation
KPI	Key Performance Indicator
LDA	Latent Dirichlet Allocation
LR	Likes Ratio
LSI	Latent Semantic Indexing
oWOM	Online Word-of-Mouth
PTATR	People Talking About That Rate
ROI	Return-On-Investment
SMM	Social Media Marketing
SNA	Social Network Analysis
SN	Social Network
SR	Shares Ratio
TD	Trend Detection
TDT	Topic Detection and Tracking
TF-IDF	Term Frequency – Inverse Document Frequency

U&G	Uses and Gratification
UGC	User-Generated Content
URL	Uniform Resource Locator
US	United States
USD	United States Dollar
WOM	Word-of-Mouth

ABSTRACT

Social networks are 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 network platforms, such as Facebook and Twitter, 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 existing examples of activities by companies and the customer's responses to them in a form of measurements and use of analysis tools. The results of such examination could increase the general understanding of this new marketing channel and identify specific methods to be applied in order to derive strategic guidelines for marketing practitioners.

To contribute in this direction, the following five studies are presented within this thesis, which address questions identified as relevant for social media marketing:

User Generated Content

Analysis of the user-generated content offers the possibility to understand the customers and explain how a certain product or a brand is perceived. This study analyses the content shared by users on Facebook brand pages in terms of topics, categories and shared sentiment. Obtained results indicate that 'Product', 'Sales' and 'Brand' are the three most discussed topics, while 'Requests and Suggestions', 'Expressing Affect' and 'Sharing' are the most common intentions for participation. In addition, positive sentiment is expressed far more often than negative.

Monitoring Trends

User-generated content on social media platforms offers the possibility to gain insights into the topics that attract the attention of a large fraction of users. This study provides a twofold contribution towards trend monitoring over Facebook public posts. A system for trend detection is proposed and evaluated. Moreover, three categories of trending topics were recognized: 'disruptive events', 'popular topics' and 'daily routines', and analyzed in terms of distribution and information diffusion in order to increase the understanding of emerging trends on Facebook. The results of the method evaluation showed that the proposed method performs well only on the most

dominant topic groups. In addition, Facebook was shown to be valuable source of news where information travels and spreads fast.

Patterns of Interaction

Social networks provide the technological platform for individuals to connect and interact with other individuals or companies. This study analyzes the activities and interactions between the members of brand communities on Facebook. Based on the obtained results, categorization of active users is proposed which distinguishes between (1) 'Posters', (2) 'Commenters', (3) 'Likers', and (4) 'Sharers'. In addition, an analysis of participation level within each of the proposed categories, and the interactions among the brand page members and the moderator are analyzed from the perspective of their evolution over time, pointing to the negative correlation to the community size.

Customer Engagement Factors

To provide insights for practitioners willing to utilize social networks for marketing purposes, this study analyses the influencing factors in terms of characteristics of the content communicated by the company, such as media type, content type, posting day and time, over the level of customer engagement measured by number of likes, comments and shares, and interaction duration for the domain of a Facebook brand page. Obtained results show that there is a significant effect of all of the analyzed factors over each of the observed engagement measures. Photos are found to be the media type that triggers the highest level of engagement. Further, posts referring to 'Fans No', 'Engagement Boosters' and 'Advertisements' are the most popular content categories. Finally, posts created between 2am and 2pm cause the largest level of user engagement.

Increasing Engagement, Loyalty, Word-of-Mouth and Community Growth

With a growing number of companies integrating social media into their marketing communications, increasing the number of fans became of interest. This study presents a coherent model which explains (1) the relation between content characteristics and engagement level, and (2) the relation between engagement, loyalty, word-of-mouth, growth and community size. Analysis shows that entertaining and informative content, as well as references to the community success, increase the engagement. In addition, vividness increases, while interactivity and post length decrease the engagement. Content should be posted on workdays and not more than once per day. Finally, pages focused on the brand as a whole and which allow fans to post on their walls achieve

the highest engagement. Finally, increasing the engagement leads to increased loyalty, volume and valence of word-of-mouth as well as community growth.

The findings of each of these studies were used to draw conclusions in a form of managerial implications which can be used as specific guidelines for social media marketing practitioners.

Finally, as an outcome of the above described studies, an evaluation framework is proposed, that allows companies to perform continuous monitoring of the content and activities on their social media marketing channels in order to measure the effectiveness of social media utilization for marketing purposes. Each framework component is based upon the results of the previously presented studies and is discussed from the perspective of the data to be used, the method to be applied and the relevance of the obtained results for social media marketing strategies. This thesis suggests that continuous utilization of the proposed framework could lead to optimization of the marketing efforts on social media platforms.

KURZFASSUNG

Soziale Netzwerke werden immer ein zusätzlicher Marketingkanal, der mit den traditionellen Marketingkanälen als Teil des Marketing-Mix integriert werden könnte. Obwohl zahlreiche Beispiele für die Verwendung von sozialen Netzwerkplattformen für Marketingzwecke, wie Facebook und Twitter bestehen, und trotz der verschiedenen Anstrengungen der Unternehmen und der allgemeinen Beliebtheit des Mediums ist die Messung der Wirksamkeit schwer fassbar.

Ein Ansatz zur Überwindung dieser Herausforderungen ist die Überprüfung der bestehenden Beispiele für die Aktivitäten der Unternehmen und der Reaktion der Kunden darauf in der Form von Messungen und Verwendung von Analyse-Tools. Die Ergebnisse einer solchen Untersuchung könnten das allgemeine Verständnis dieses neuen Marketingkanals erhöhen und bestimmte anwendbare Methoden identifizieren, um daraus strategische Leitlinien für die Marketingpraktiker abzuleiten.

Um in dieser Richtung beizutragen, werden die folgenden fünf Studien im Rahmen dieser Dissertation dargestellt, die die Fragen erörtern, die als relevant für Social Media Marketing identifiziert wurden:

Nutzergenerierte Inhalte

Die Analyse der nutzergenerierten Inhalte bietet die Möglichkeit die Kunden zu verstehen und zu erklären, wie ein bestimmtes Produkt oder eine Marke wahrgenommen wird. Diese Studie analysiert den Inhalt, der von Nutzern auf Facebook-Markenseiten im Bezug auf Themen, Kategorien und geäußerten Empfindungen geteilt wurde. Die erhaltenen Ergebnisse zeigen, dass Produkt, Vertrieb und Marke die drei am meisten diskutierten Themen sind, wobei Anfragen und Empfehlungen, Gefühlsausdruck und Veröffentlichung die häufigsten Absichten für die Teilnahme sind. Darüber hinaus werden die positiven Empfindungen weit häufiger als die negativen zum Ausdruck gebracht.

Trend-Monitoring

Die nutzergenerirten Inhalte auf sozialen Netzwerkplattformen bieten die Möglichkeit einen Einblick in die Themen, die die Aufmerksamkeit eines großen Teils der Nutzer anziehen, zu gewinnen. Diese Studie liefert einen doppelten Beitrag zur Trend-Monitoring über die öffentlichen Facebook-Beiträge. Es wird ein System zur Trenderkennung vorgeschlagen und ausgewertet. Darüber hinaus wurden drei Kategorien von Trendthemen

erkannt und zwar „störende Ereignisse“, „populäre Themen“ und „Alltag“ und analysiert im Bezug auf die Verteilung und Verbreitung von Informationen, um das Verständnis der aufkommenden Trendthemen auf Facebook zu erhöhen. Die Ergebnisse der Verfahrensauswertung ergaben, dass das vorgeschlagene Verfahren nur für die beherrschenden Themengruppen gut funktioniert. Darüber hinaus wurde gezeigt, dass Facebook eine wertvolle Quelle von Nachrichten ist, wo Informationen sich sehr schnell verbreiten.

Interaktionsmuster

Die sozialen Netzwerke bieten die technologische Plattform für den Einzelnen sich mit anderen Personen oder Unternehmen in Verbindung zu setzen und zu kommunizieren. Diese Studie analysiert die Aktivitäten und die Wechselwirkungen zwischen den Mitgliedern der Marken-Gemeinschaften auf Facebook. Aufgrund der erhaltenen Ergebnisse wurde eine Kategorisierung der aktiven Benutzer vorgeschlagen, die ein Unterschied zwischen (1) posters, (2) commenters, (3) likers, und (4) sharers macht. Darüber hinaus wurde eine Analyse des Beteiligungsgrades innerhalb jeder der vorgeschlagenen Kategorien und der Wechselwirkungen zwischen den Markenseiten-Mitglieder und dem Moderator im Bezug auf ihre Entwicklung im Laufe der Zeit durchgeführt, wobei auf die negative Korrelation zu der Größe der Gemeinschaft aufmerksam gemacht wird.

Faktoren für Kundenengagement

Um Erkenntnisse für Praktiker, die soziale Netzwerke für Marketingzwecke nutzen möchten, bereit zu stellen, analysiert diese Studie die Einflussfaktoren im Sinne von Eigenschaften des vom Unternehmen übermittelten Inhaltes, wie Medientyp, Inhalt, Tag und Uhrzeit des Beitrages über den Grad des Kundenengagements, das über die Anzahl der Likes, Kommentare und Veröffentlichungen und die Interaktiondauer für die Domain einer Facebook-Markenseite gemessen wird. Die erhaltenen Ergebnisse zeigen, dass es eine signifikante Wirkung aller analysierten Faktoren auf allen beobachteten Engagementmaßnahmen besteht. Es kam vor, dass die Fotos der Medientyp sind, der den größten Maß an Engagement auslöst. Weiterhin, die Beiträge, die sich auf Anzahl von Fans, Engagement-Boosters und Anzeigen beziehen, sind die beliebtesten Inhaltkategorien. Und schließlich, die zwischen 02:00 und 14:00 Uhr geteilten Beiträge schaffen den größten Grad des Benutzer-Engagements.

Zunehmendes Engagement, Loyalität, Mundpropaganda und Community-Wachstum

Im Hinblick auf die wachsende Zahl von Unternehmen, die soziale Medien in ihre Marketing-Kommunikation integrieren, hat die Erhöhung der Anzahl der Fans das Interesse geweckt. Diese Studie stellt ein kohärentes Modell dar, das (1) das Verhältnis zwischen den Eigenschaften des Inhaltes und dem Engagementgrad und (2) die Beziehung zwischen Engagement, Loyalität, Mundpropagand, Wachstum und Gemeinschaft -Größe erklärt. Die Analyse zeigt, dass die unterhaltsame und informative Inhalte, sowie Verweise auf den Erfolg der Community das Engagement erhöhen. Darüber hinaus die Lebhaftkeit erhöht, und die Interaktivität und die Länge des Beitrages verringern das Engagement. Inhalte sollen an Werktagen und nicht mehr als einmal pro Tag geteilt werden. Schließlich, die Seiten die sich auf die Marke als Ganzes konzentrieren und die den Fans erlauben, auf ihre Wände Beiträge zu teilen, erreichen das höchste Engagement. Abschließend führt die Zunahme des Engagements zu einer erhöhten Loyalität, Volumen und Wertigkeit der Mundpropagand, sowie zum Community-Wachstum.

Die Ergebnisse der beiden Studien wurden genutzt um Schlussfolgerungen in Form von Managementimplikationen zu ziehen, die als Leitlinien für die SMM-Praktiker verwendet werden können. Als Ergebnis der oben beschriebenen Studien wird abschließend einen Evaluierungsrahmen vorgeschlagen, der es den Unternehmen ermöglicht, eine kontinuierliche Überwachung der Inhalte und Aktivitäten auf ihre Social-Media-Marketing-Kanäle durchzuführen, um die Wirksamkeit der Social-Media-Nutzung für Marketingzwecke zu messen. Alle Komponenten des Rahmens basieren sich auf die Ergebnisse der bisher vorgestellten Studien und werden aus der Perspektive der verwendbaren Daten, des anwendbaren Verfahrens und die Relevanz der eingeholten Ergebnisse für Social Media Marketing-Strategien diskutiert. Diese Arbeit lässt vermuten, dass eine kontinuierliche Nutzung des vorgeschlagenen Rahmens zu einer Optimierung der Marketing-Bemühungen auf den sozialen Netzwerkplattformen führen könnte.

DISSERTATION

1. Introduction

Marketing has recently undergone significant changes in the way information is delivered to the customers (Mangold and Faulds 2009, pp. 357-365). Social media platforms have offered the possibility to overcome the traditional one-way communication by providing technological platforms which support dialog between the consumers and the companies (Hanna et al. 2011, pp. 265-273). As a result of this change, many challenges were faced upon the marketing practitioners (Bolotaeva and Cata 2010), resulting in numerous questions to be answered. Among others, a question that attracted the attention of scholars and practitioners is: How to evaluate the effectiveness of social media marketing? Studies and results presented in this thesis were conducted with a goal of providing an answer to this question.

1.1. Motivation

To provide a background and explain the motivation for the research conducted as a part of this thesis, this section provides an overview of the history of social media marketing, explains the state of the art in the domain, and elaborates the challenges faced upon the marketing practitioners.

1.1.1. The Rise of Social Media Marketing

The emergence of the Web 2.0 has changed the way content is generated on the web. Rather than being just passive consumers, users have become active participants by sharing information, experiences and opinions with each other. Social media, as a group of Internet-based applications that build on the foundations of Web 2.0, provides the possibility for individuals to connect, produce and share content online (Kaplan and Haenlein 2010, pp. 59-68). As such, for brand owners, it offers 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, pp. 89-103).

The rise and continued growth of social media platforms have attracted the interest of companies who see the potential to transmit their marketing messages to the customers and enter into a dialogue with them using word-of-mouth (WOM) principles, thus gaining a better understanding of their customers (Hanna et al. 2011, pp. 265-273). As an outcome of this change in the field of marketing, a new phenomenon known as social media marketing (SMM) was introduced.

SMM, a form of WOM marketing, but also known as viral marketing, buzz, and guerilla marketing, is the intentional influencing of consumer-to-consumer communication through professional marketing techniques (Kozinets et al. 2010, pp. 71-89). 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, pp. 357-365). The advantage of this new electronic channel is that it can be used to communicate globally and to enrich marketing towards consumers at personal level (Brandt 2008, pp. 28-33). Through users' feedback or by observing conversations on social networks, 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, pp. 162-176).

1.1.2. State of the Art

Companies, across all industries, are starting to understand the possibilities of social media marketing. They have evolved their customer approach, shifting from traditional "one-to-many" communication to a "many-to-many" approach, and offering contact or assistance at any time through various social media platforms, such as blogs, social networks, etc. (Berthon et al. 2007, pp. 39-48). Using the social network Facebook[1] as an example, this means that companies set up and moderate a "Facebook brand page" while continuously monitoring the consumers' activities (see Chapter 3: "Facebook as a Platform for Social Media Marketing" for details).

With the growing number of users and activities on social media platforms, the number of companies that embrace SMM as a part of their marketing campaigns is also increasing. According to a study conducted by Social Media Examiner (Stelzner 2012), 94% of the companies employ one or more social

[1] Facebook. http://www.facebook.com/. Accessed 2012-07-18

media platforms for marketing purposes. At the same time, the number of brand followers on social media platforms is also increasing, for example, in US, the percentage of brand followers grew from 16% in 2010 to 33% in 2012[2].

Still, differences in social media adoption and utilization exist between different industry domains in terms of the number of fans they attracted, as well as in the level of engagement within these platforms, as two most popular measures of success. For example, Fast Moving Consumer Goods (FMCG) are found to be the leading industry domain on Facebook, with an average of 2'296'740 fans on their brand pages, yet the last one according to the level of engagement[3]. Figure 1 illustrates these differences.

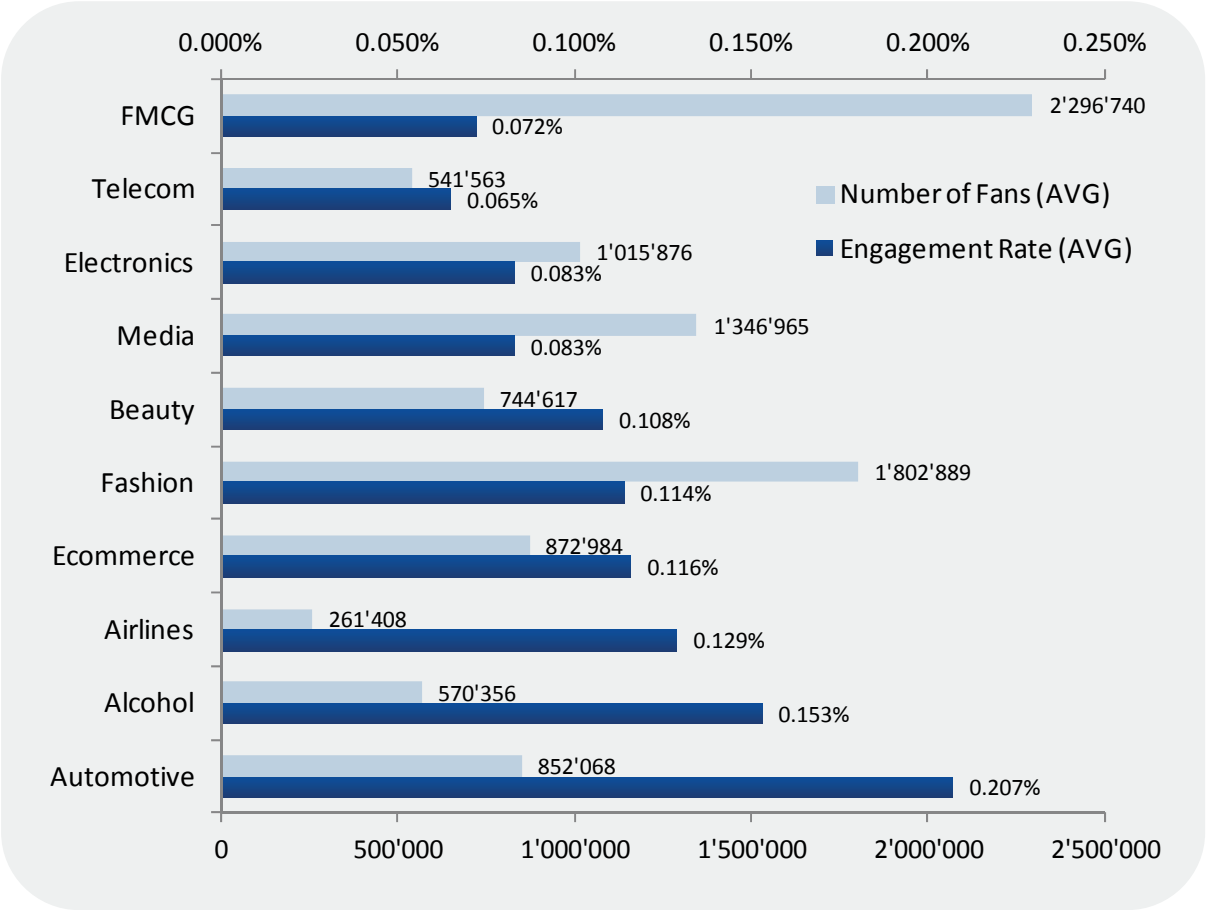

Figure 1: Facebook industries by average engagement rate (January to March 2012)[3]

[2] 11 Shocking New Social Media Statistics in America. http://www.convinceandconvert.com/the-social-habit/11-shocking-new-social-media-statistics-in-america/. Accessed 2012-08-20

[3] Finally here! The Biggest Global Social Media Report on Facebook Industries. http://www.socialbakers.com/blog/527-finally-here-the-biggest-global-social-media-report-on-facebook-industries. Accessed 2012-09-20

Despite the popularity, viral marketing on social media platforms has not yet reached the high expectations set (Clemons et al. 2007, pp. 267-276). This is partially due to the newness of the communication medium and the lack of understanding of the consumers and their motives for participation in brand related conversation on social media platforms (Richter et al. 2011, pp. 89-103). As an outcome, a perception gap regarding the priorities of consumers and marketers occurred (IBM 2011; Pivot 2012), which might lead to inappropriate approach of companies towards their fans on SMM channels.

In addition, the number of academic studies in the field, which might contribute to the general understanding of the medium and provide guidelines for its successful utilization, is still relatively small, thus providing only limited support to the practitioners (Richter et al. 2011, pp. 89-103; Wilson et al. 2012, pp. 203-220).

1.1.3. Problem

The above presented overview of the state of the art in the field of social media marketing indicates existence of several problems faced upon marketers interested in SMM. This section provides an overview of the three recognized domains.

1.1.3.1. Lack of Understanding of the Communication Medium

Today, on account of the newness and lack of knowledge, companies experiment with many different forms of interaction (Coon 2010). This approach sometimes results in a great success, but in other cases leads to failure, which might destroy the brand image.

For example, Coca-Cola managed to build the largest brand community on Facebook by employing a strategy which integrated all existing, Coca-Cola related, brand pages and focusing on the brand as a whole, instead on a single product. In addition, Coca-Cola supports viral marketing by asking the page members to create and share entertaining content, thus increasing the brand awareness[4]. Another successful example is the Christmas ad campaign by Nutella, which showed that marketing efforts on Facebook can outperform the

[4] How Coca-Cola Has Cultivated the Biggest Facebook Brand Page. http://www.ragan.com/Main/Articles/44132.aspx. Accessed 2012-08-20

traditional campaigns, resulting in greater sales[5]. Moreover, Toyota showed that even when the brand's reputation is threatened by external factors, appropriate social media approach might help the company gain new supporters[6].

By contrast, Wal-Mart's initial attempt to join Facebook ended with failure due to an inappropriate communication tone, focusing on marketing messages instead on social interaction, and preventing fans to join discussions threads[7]. Similarly, poor understanding of the medium at Nestle damaged the brand when a consumer post about the destruction caused by palm oil forestation was answered by a belligerent company representative with several hours of delay. Furthermore, when the discussion continued, the only reaction from Nestle was to delete the negative content created by the consumers, which lead to flood of additional reactions from the fans, ultimately transporting the problem to mainstream media (Fournier and Avery 2011, pp. 193-207).

These examples indicate that although social media is massively used for marketing, what the potentials of this medium are, and how consumers interact, remains largely unknown (Richter et al. 2011, pp. 89-103).

1.1.3.2. Lack of Established Strategies

Examination of the existing examples of activities by companies and the customer's responses to them are of high interest to the marketers and therefore a subject to close examination in the form of measurements and use of analysis tools. This results in numerous "social media strategies" which recommend the "best practises" for creation of social media brand presence and engagement in brand related dialog with the consumers.

Still, looking at the proposed strategies, great diversity can be observed in the given recommendations. For example, in terms of frequency of posting, some practitioners only suggest finding the optimal frequency, without proposing a

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[5] Case Study: Nutella Facebook Ad Campaign Outperforms TV. http://www.simplyzesty.com/facebook/case-study-nutella-facebook-ad-campaign-outperforms-tv/. Accessed 2012-08-20

[6] How Toyota Used Social Media To "Digg" Itself Out of a PR Nightmare. http://mashable.com/2011/09/01/toyota-digg-recalls/. Accessed at: 2012-08-20

[7] A Failed Facebook Marketing Campaign. http://social-media-optimization.com/2007/10/a-failed-facebook-marketing-campaign/. Accessed 2012-08-08

method to be used for its selection[8]. In turn, others provide more specific answers but with large variations in the proposed values, e.g. from "three times per hour"[9] to "once every other day"[10]. In addition, these articles and reports rarely provide information on the dataset which was used to derive the guidelines, such as the type of the analyzed brand, demographics of the community members, etc., which are all factors that might influence the obtained results.

Therefore, a structured academic analysis in this field, based on empirical studies, is still outstanding and has yet to be addressed from different perspectives (Wilson et al. 2012, pp. 203-220).

1.1.3.3. Lack of Methods for Effectiveness Evaluation

Despite the various efforts from the companies and the general popularity of the medium, measuring the effectiveness is elusive (Shankar and Hollinger 2007). Some small cases have been reported, such as the Houston bakery chain, that increased customer frequency in their stores thanks to the carefully managed Facebook advertising campaign (Dholakia and Durham 2010, pp. 26). In addition, an experiment regarding the effectiveness of company-driven WOM communication showed that this can increase sales (Godes and Mayzlin 2009, pp. 545-560).

The observed situation is partially due to the absence of clear objectives and goals which would define the measures and methods to be used, as well as the concept of "success" (Dubach Spiegler 2011). This is mostly a result of the relatively limited knowledge about the rules of communication on this new medium (Richter et al. 2011, pp. 89-103) and the attempt to transfer the existing theories and practices from traditional marketing to SMM (Hoffman and Fodor 2010, pp. 41-49).

This thesis aims at closing the gap in the literature that leaves the problems of understanding the usage of social media platforms for marketing purposes,

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[8] 10 Tips for Posting on Your Brand's Facebook Page. http://mashable.com/2011/03/22/tips-brand-facebook-page/. Accessed 2012-08-08

[9] Facebook Pages Shouldn't Post More Than 1x Every 3 Hours. http://techcrunch.com/2012/01/17/how-often-should-facebook-pages-post/. Accessed 2012-06-12

[10] New Data: Post to Your Facebook Page Every Other Day for the Most Likes. http://danzarrella.com/new-data-post-to-your-facebook-page-every-other-day-for-the-most-likes.html. Accessed 2012-06-12

and supporting the companies in the task of effectiveness evaluation of their social media utilization, through continuous monitoring of the content and activities on their social media channels.

To contribute in this direction, based on the results obtained from empirical studies, an evaluation framework is proposed (see Chapter 9: "Evaluation Framework for Social Media Brand Presence"). Continuous utilization of the proposed framework would enable early problem detection, thus providing the possibility for timely reaction of the companies in a form of strategy adaptation in accordance with the specific characteristics of their brand communities.

1.2. Research Questions and Contributions

The previous section presented and discussed some of the challenges faced upon practitioners interested in utilizing social media platforms for marketing purposes. These challenges can be summarized in the following three problem domains:

- Understanding the usage of social media platforms;
- Defining social media strategies; and
- Effectiveness evaluation of marketing efforts.

The above listed problems are interconnected, i.e. by understanding the way consumers engage with brands on social media platforms, list of implications for practitioners can be derived, which could further be used for creation of engagement strategies. In addition, continuous measurement through methods applied for analysis can be used for effectiveness evaluation.

In the continuation, this reasoning will be formulated as a research question and will further be elaborated by identifying related sub-questions.

1.2.1. Research Questions

To address the previously described problem, the main research question which will be answered in this thesis is:

How to evaluate the effectiveness of social media marketing?

In order to answer this question, an understanding of the usage of existing brand pages is gained through analysis of different elements that describe the utilization of social media for marketing purposes.

As a first step towards identifying the specific elements of SMM to be investigated, a review of existing literature was performed (see Chapter 2: "Related Work" for details). Based on this review, several specific domains which are of interest for academia and practitioners were identified, which can further be grouped into three main research areas: (1) user-generated content, (2) users of SMM platforms, and (3) engagement on SMM platforms. In the continuation each of these areas will be detailed and specific sub-questions will be formulated.

1.2.1.1. User-Generated Content on Social Media Platforms

User-generated content (UGC) is the main outcome of consumers' engagement on social media platforms. As such, classification of the UGC could allow companies to perform market analysis and rumour detection. In addition, automatic extraction of aggregated information from the UGC shared outside the SMM channels enables monitoring of the brand image and benchmarking against competitors. Thus this research is further divided into two separate problems.

Listening to Conversation on Social Media Marketing Channels

Communication on SMM platforms might differ, depending on the type of offered product or service. Therefore, companies should analyze the UGC created on their SMM channels in order to understanding the customers and build an appropriate communication plan. To gain a better understanding of the UGC on social media platforms, the following questions are answered in this thesis:

RQ1: What are the topics of conversation?

Understanding the topics of conversation could bring benefits in terms of organization of the team behind the social media channel that could provide timely answers to users, as expected on social media platforms. In addition, it would bring direct insights into customers' opinions, without the need to conduct costly market analysis.

RQ2: What are the intentions for participation in brand communities on social media?

Understanding the intentions for participation could provide insights into: how to attract more users, and how to engage with them appropriately, by offering content which is of interest to them.

RQ3: Which emotions are shared within the UGC and how?

Sentiment analysis is one of the most interesting questions for companies and brand owners. It reveals the perception of the products and/or services by their customers, i.e. the brand attitude. In addition, monitoring of the sentiment fluctuations over time can be used as a measure for success.

Monitoring Trends on Social Media Platforms

Buzz monitoring, as a simple count of mentions, was found to be a relatively inaccurate method for monitoring the brand related communications. Thus applying text mining techniques over a large amount of unstructured UGC would yield more accurate results. In order to gain a better understanding on the available methods for automatic UGC analysis, the following question is answered in this thesis:

RQ4: How to monitor trends over the UGC on social media?

Apart from observing their own social media channels, companies should listen to the conversation on a global level in order to monitor trends which in turn could provide them the possibility to stay in line with their competitors. Thus finding out which methods can be used to automate this process could help practitioners achieve their goals.

RQ5: What are the characteristics of trending topics?

Classification of trending topics might be useful to select the most appropriate topics to be communicated through the SMM platforms. In addition, understanding the differences between the trending topics, in the form of temporal distribution, provides the possibility for automatic content classification and for selection of the suitable time for posting.

1.2.1.2. Users of Social Media Marketing Platforms

Customers who engage with brands through social media platforms are at the core of SMM efforts. Thus, understanding the users of SMM platforms is an important component for optimization of the marketing efforts. In order to

gain a better understanding of the users, the following questions are answered in this thesis:

RQ6: What are the interaction patterns on social media platforms?

Identifying and understanding the differences between the users in terms of interaction patterns on social media platforms could provide the possibility to approach them appropriately through proactive moderation. In addition, this approach could reveal the most enthusiastic users which could then be addressed directly.

RQ7: What are the characteristics of the social network created between the users of social media platforms?

Answering this question would provide knowledge about the structural characteristics of the brand communities, their evolution over time and dependency from the community size. In addition, the obtained results would provide the possibility to identify the critical points in the network, as well as the influential fans. Finally, it will reveal the importance of the "company's voice" for the brand community.

1.2.1.3. Engagement on Social Media Platforms

Customer engagement is the new key metrics for success of SMM campaigns. In order to increase the level of engagement, companies need to build an engagement plan before engaging in SMM in order to avoid failures by appropriately approaching their fans. In order to gain a better understanding of the effect of the moderator actions over the level of engagement, as well as to estimate the value of the concept of engagement, the following questions are answered in this thesis:

RQ8: Which factors influence the level of engagement on SMM platforms?

Since there are no proven guidelines on how to interact with the users, an evaluation is needed to estimate what interactions, content, and features will keep fans coming back.

RQ9: What is the relation between the engagement, loyalty, word-of-mouth and growth on SMM platforms?

Estimating the relation between the marketing constructs and engagement could provide confirmation of the value of increasing the engagement on social media platforms. In addition, it could provide

possibility for prediction, for example of the community growth, based on the undertaken engagement actions.

1.2.1.4. Effectiveness Evaluation

Once an overall understanding of the usage of social media platforms for marketing purposes has been gained, based on the obtained results, implications can be derived for social media practitioners, which have a direct influence over the elements of SMM strategies. These implications can be used to create an initial SMM strategy.

Further, since brand communities on social media might differ from each other, it is important for companies to perform continuous monitoring of the undertaken actions and customers' responses to them in order to gain knowledge about the specific characteristics and interests of their own brand communities. This in turn enables fine-tuning of the initially established SMM strategy. Therefore, the final contribution of this thesis is to provide an answer to the following question:

RQ10:How to evaluate the effectiveness of social media marketing?

Due to the lack of existing guidelines, an investigation should be performed to estimate which existing analysis methods are available and applicable for effectiveness evaluation in terms of analysis of the performance of a brand page in the three fields described as building blocks for the previous question.

Answering the previously listed questions leads to creation of evaluation framework which should be utilized by the companies in order to monitor and measure their performance on social media as an emerging marketing channel.

1.2.2. Contributions

The contribution of this thesis consists of several elements. First, answering the research questions presented in the previous section leads towards increasing the understanding of the utilization of social media platforms for marketing purposes. Moreover, specific methods are proposed which enable analysis of the data obtained from SMM channels. Finally, based on the obtained results, implications for marketing practitioners are drawn, which can serve as guidelines for efficient SMM.

As a final outcome of this thesis, representing a summary of the above listed contributions, a framework for evaluation of effectiveness of SMM efforts is

proposed (see Chapter 9: “Evaluation Framework for Social Media Brand Presence”). This framework is consisted of four components which are detailed on the level of data sources to be used, methods to be applied for analysis, and the relevance of obtained results for SMM strategies. As such, it provides a contribution for academia and practitioners by closing the identified research gap and providing an applicable solution for practitioners.

To answer each of the above listed sub-questions, five studies were undertaken. The individual contribution of each of these studies is summarized in continuation.

1.2.2.1. User Generated Content on Facebook Brand Pages

The contribution of this study is that it overcomes the problem of lack of understanding of the UGC shared on Facebook brand pages as SMM platform by providing insights into the discussed topics and intentions for participation. In addition, Facebook brand pages were shown to be a platform where positive sentiment is shared far more often compared to the negative, thus making them a suitable platform for marketing.

From marketers’ perspective this study suggests that Facebook brand pages provide the possibility for generation of ideas about new products and services, it points out to the need for support board behind the moderator, and reveals the possibility to use the topic-category matrix as a measure for effectiveness over time.

1.2.2.2. Monitoring Trends on Facebook

The main contribution of this study consists of providing a solution for monitoring trends on Facebook which was not previously available. The proposed solution overcomes the challenges of data collection, originating from the existing privacy policies on Facebook, and the lack of support from Facebook as a platform provider. In addition, it overcomes the challenge of extracting information from short unstructured text shared on Facebook.

The study further contributes by increasing the understanding of characteristics of the trending topics by proposing a categorization, and investigating the distribution, speed and flow of information on Facebook.

1.2.2.3. Understanding the Patterns of Interaction

The contribution of this study is that it proposes new user classification scheme, based on the engagement patterns. In addition, it points out to the correlation between the level of engagement and community size, thus

providing support for existing theories from the fields of sociology and brand community participation.

Based on the obtained results, practical implications for social media marketing were drawn which can be used to prepare Facebook brand page communication strategies.

1.2.2.4. Customer Engagement on Facebook Brand Pages

This study represents an investigation of the factors that influence the level of engagement over the content shared by a company on a Facebook brand page. As such, it provides contribution by increasing the understanding of the concept of engagement on social media platforms, through revealing the role of the content category, post media type, weekday and time of posting as engagement factors.

Based on the obtained results clear implications were drawn for SMM practitioners, which point out to the importance of preparation of posting strategies and expose the specific content characteristics that trigger the activity of users.

1.2.2.5. Increasing Engagement, Loyalty, Word-of-Mouth and Growth on Facebook Brand Pages

This study contributes to the field of marketing by developing a coherent model which explains: (1) the relation between individual content characteristics as factors that influence the level of brand engagement, and (2) the relation between engagement and (a) loyalty, (b) WOM communication, (c) growth and (d) community size. In addition, a translation of the classical marketing constructs into the domain of a Facebook brand page is proposed. The proposed model was empirically evaluated, based on the large dataset consisted of all activities over two months on the top 100 Facebook brand pages in the Food/Beverages category.

From practitioners' perspective, the proposed model provides a toll to be used to predict the success of marketing efforts in terms of engagement level, which can further be used to estimate the number of returning (loyal) fans, the volume and valence of WOM communication and the community growth.

Figure 2 summarizes the previous discussion by pointing to the relation between the research questions and their contributions which lead towards answering of the main research question.

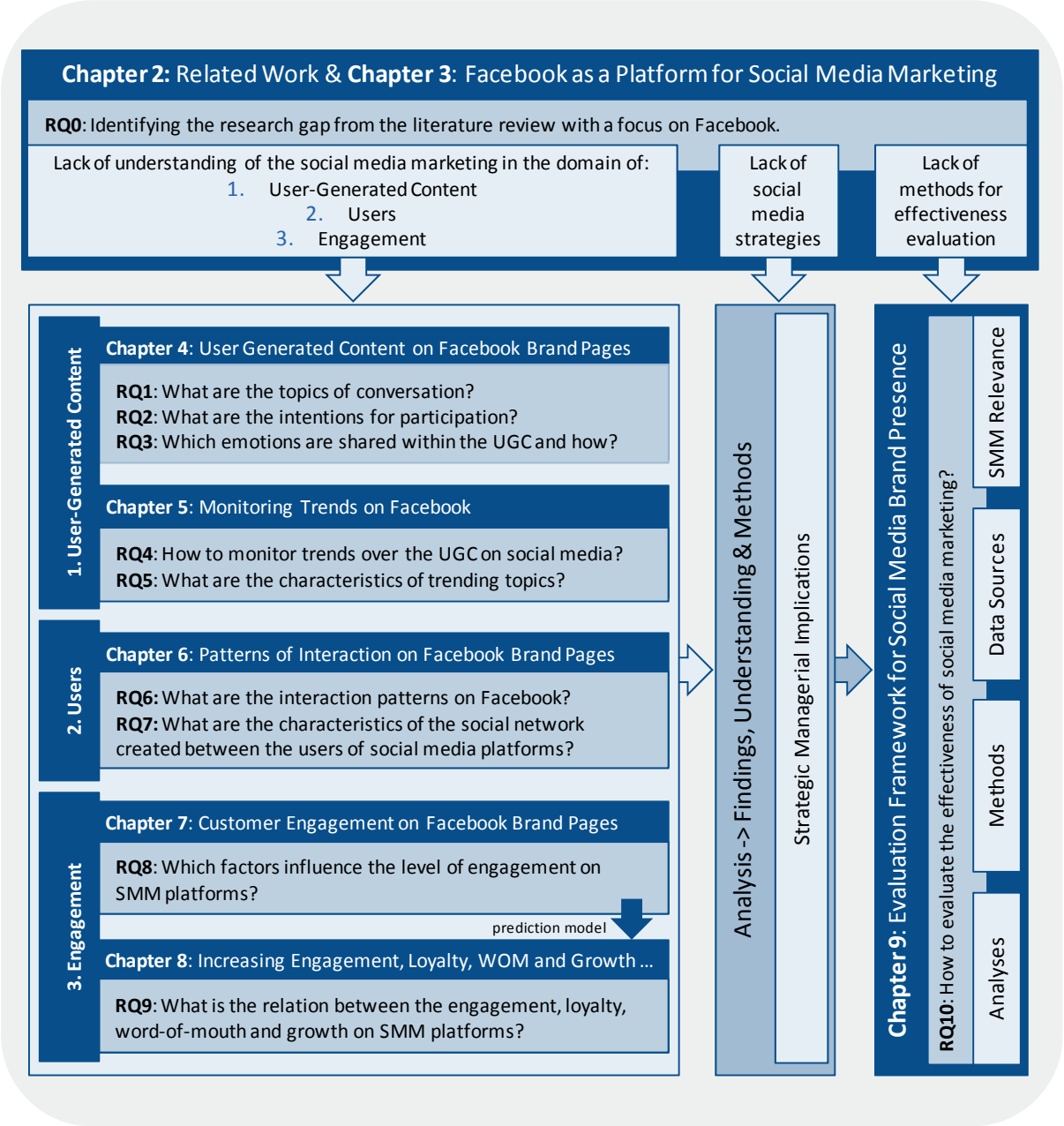

Figure 2: Organization of the thesis

1.3. Research Methodology

Answering of the research questions of this thesis is approached with a combination of research methods.

Due to the lack of existing work in the field, an exploratory approach was undertaken for the analysis of the UGC on Facebook brand pages and the analysis of the interactions among the community members. In addition, due to the high level of details in the observed datasets, both studies were conducted as case studies. For the analysis of the UGC, this approach provided

the possibility for qualitative in-depth investigation of the content, thus revealing a greater level of details, while for the social interactions, a longitudinal approach over a single Facebook brand page provided insights into the evolution of the interaction level over time.

To propose a solution for monitoring trends on Facebook, text mining (see Chapter 5: “Monitoring Trends on Facebook” for details) was employed, based on a novel algorithm and over a large dataset consisted of Facebook public posts. Evaluation of the proposed algorithm was based on the commonly used approach of precision and recall calculation.

Finally, engagement on Facebook brand pages and its relation to traditional marketing constructs were studied over a large dataset, by applying a confirmatory data analysis, i.e. statistical hypothesis testing.

Details of the above listed methods are further elaborated in the continuation of this thesis, in the respective chapters for each of the conducted studies.

1.4. Research Context and Boundaries

Social media refers to a large variety of existing Web 2.0 technological platforms. As such, to marketers it offers different engagement possibilities with their customers, resulting in different formats of UGC. Furthermore, companies which are interested in social media utilization for marketing purposes vary in the type of offered products and services. Thus conducting a study which would cover all social media platforms and all types of offered products and services would be unfeasible.

For that reason, this thesis is bounded by two main limitations: (1) selection of the social network Facebook as a social media platform, and (2) selection of FMCG as a product category to be studied. These two limitations are detailed in the continuation.

1.4.1. Facebook as a Platform for Social Media Marketing

Social networks currently represent the most popular category of social media platforms (see Chapter 2.1: “Social Media Platforms” for details). Moreover, at the time of writing, Facebook is the largest social network, attracting a great attention of individuals and marketers, visible through the number of individual users, and the number of companies utilizing Facebook to engage in

brand related dialog with their consumers who have created Facebook profiles[11]. Chapter 3: “Facebook as a Platform for Social Media Marketing” provides additional details over the perceived importance of Facebook as a marketing platform from the practitioners’ perspective. The large numbers of users and activities on Facebook have also attracted the interest of scholars, resulting in Facebook being on the top position of studied social media platforms, measured by the number of publications (Richter et al. 2011, pp. 89-103). These two facts were used as a basis for selection of Facebook as a platform to be studied within this thesis.

The used terminology and studies presented in the continuation of this thesis reflect the choice of Facebook as an underlying platform. An attempt was made to use concepts, such as brand community members, engagement or moderation, which are basic to any social media platform, in order to enable translation of the findings to other existing or emerging platforms, in particular to other social networks. Still, the selection of Facebook represents a clear limitation of this thesis.

1.4.2. Fast-Moving Consumer Goods as a Product Category

A specific group of brands which were studied as a part of this thesis are those offering Fast-Moving Consumer Goods products. The selection of this product category was based on the possibility to establish collaboration with a Swiss retailer Valora[12], which enabled access to the complete usage data of their Facebook brand page (see Chapter 3: “Facebook as a Platform for Social Media Marketing” for details on the data availability).

The brand ok.-[13] was created as “good and affordable” brand, offering “useful products and services which make everyday life more enjoyable”. The advertising slogan "... is totally ok.-" soon reached the younger consumers, which became apparent on the company’s Facebook brand page[14], launched in March 2010. At the time of writing, the page counts 118,759[15] members with an ongoing and active discussion of the wall.

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[11] Alexa: Top Sites. http://www.alexa.com/topsites. Accessed 2012-09-19

[12] Valora. http://www.valora.com/en/index.php. Accessed on 2012-08-12

[13] ok.-. http://www.okpunktstrich.ch/. Accessed on 2012-08-21

[14] okPunktStrich. http://www.facebook.com/okPunktStrich. Accessed 2012-07-11

[15] Obtained on 2012-09-20

To maintain consistency in the obtained results, for the further analysis conducted over a larger number of brand pages, the same industry domain was selected. This industry domain is represented on Facebook under the *Food/Beverages* brand page category. Although some of the findings are general and as such applicable to any product type, such as the effect of media type over the level of engagement, certain findings, such as those referring to the topics of conversation, are specific for this particular product category. It should be noted that this approach provides more detailed overview over a single product type. In addition, due to the different interests of members of different brand communities, same rules might not apply for all product types. Thus, limiting the analysis to one product type avoids possible errors and misinterpretation of the obtained results. Nonetheless, selection of FMCG as industry domain to be studied represents a limitation of this thesis.

1.5. Thesis Outline

The continuation of this thesis is organized as follows:

Chapter 2 reviews the existing studies from the relevant fields: social media and social networks, virtual brand communities, user-generated content, word-of-mouth communication and social media marketing. As an outcome, the research gap is identified, detailed as a list of problem domains relevant for academia and practitioners.

Chapter 3 provides background information for the selected social media platform – the social network Facebook. It introduces the basic terminology and elaborates on the available marketing possibilities, with a focus on Facebook brand pages. Finally, a brief overview is given on existing social media strategies.

Chapter 4 presents a study conducted in order to understand the UGC on Facebook brand pages. The obtained results reveal the topics referred to within the UGC, intentions for participation and the volume and valence of the shared sentiment. Based on the presented findings, implications for marketing practitioners are drawn.

Chapter 5 introduces and evaluates a method for monitoring trends on Facebook, consisted of algorithms for data collection and topic identification. Based on the collected dataset, an analysis of the trends on Facebook is provided, revealing differences between

trends, proposing a categorization scheme, and investigating the distribution, speed and flow of trending topics.

Chapter 6 explains the interaction patterns between the moderator and the community members on Facebook brand pages. A classification scheme is proposed, based on the engagement patterns, and a longitudinal analysis of the interactions among the fans is performed. Based on the obtained results, implications for social media marketing are drawn.

Chapter 7 presents a study of the effect of the characteristics of the content, shared by a company on Facebook brand pages, i.e. the content categories, post media type, posting weekday and time, over the level of user engagement, measured through the undertaken actions, i.e., comments, likes and shares. A detailed analysis of each engagement factor is performed, in order to derive implications for practitioners.

Chapter 8 proposes a coherent model which explains: the relation between content characteristics as factors that influence the level of brand engagement on Facebook, and the relation between engagement and loyalty, WOM, growth and community size. In addition, a translation of the classical marketing constructs into the domain of a Facebook brand page is provided. The results of the empirical evaluation are used to draw implications for practitioners.

Chapter 9 proposes a novel evaluation framework for monitoring and measuring the effectiveness of social media utilization for marketing purposes. A detailed description of the specific methods to be used, for each of the identified actions to be undertaken during the evaluation process, is given. The value of the obtained results is discussed from the perspective of the moderation policy.

Chapter 10 summarizes the most important results of this thesis in a form of contributions for academia and implications for marketers. In addition, it presents how the research questions were answered, identifies the limitations and proposes directions for future research.

Summary of Main Points

- Identified problems in the domain of social media marketing:
  - Lack of general understanding of the social media as a marketing platform.
  - Lack of established social media strategies.
  - Lack of established methods for effectiveness evaluation.
- Research questions to be addressed:
  - RQ1: What are the topics of conversation?
  - RQ2: What are the intentions for participation in brand communities on social media?
  - RQ3: Which emotions are shared within the UGC and how?
  - RQ4: How to monitor trends over the UGC on social media?
  - RQ5: What are the characteristics of trending topics?
  - RQ6: What are the interaction patterns on social media platforms?
  - RQ7: What are the characteristics of the social network created between the users of social media platforms?
  - RQ8: Which factors influence the level of engagement on SMM platforms?
  - RQ9: What is the relation between the consumer engagement and loyalty, word-of-mouth and brand awareness on SMM platforms?
  - RQ10: How to evaluate the effectiveness of social media marketing?

Outcome:

Evaluation Framework for Social Media Brand Presence

2. Related Work

The work presented in this dissertation is focused on utilization of social media platforms for marketing purposes. To provide a background for the research presented in the following chapters, this chapter reviews the existing academic work from the relevant fields: social media and social networks as the largest social media platform, existence and characteristics of virtual communities among admirers of a brand, the outcome of brand community participation in the form of user-generated content, distribution of user-generated content among consumers in the form of word-of-mouth communication and finally, social media marketing as a new marketing phenomena whose foundations are laid on the existence of brand communities on social media platforms with a goal of engaging the consumers in a brand related communication, which results in user-generated content and word-of-mouth communication.

Parts of this section were initially published or submitted as a part of the following academic papers: “Understanding Social Media Marketing: A Case Study on Topics, Categories and Sentiment on a Facebook Brand Page” (Pletikosa Cvijikj and Michahelles 2011d, pp. 175-182), “Understanding the User Generated Content and Interactions on a Facebook Brand Page” (Pletikosa Cvijikj and Michahelles 2013), “Monitoring Trends on Facebook” (Pletikosa and Michahelles 2011a, pp. 895-902), “A case study of the effects of moderator posts within a Facebook brand page” (Pletikosa Cvijikj and Michahelles 2011b, pp. 161-170), “The Effect of Post Type, Category and Posting Day on User Interaction Level on Facebook” (Pletikosa Cvijikj et al. 2011c, pp. 810-813), “Evaluation Framework for Social Media Brand Presence” (Pletikosa Cvijikj et al. 2013a), and “Increasing brand engagement, loyalty and growth among consumers on Facebook brand pages: An empirically supported model”(Pletikosa Cvijikj et al. 2013b). Thus this section contains excerpts from the previously referenced publications which are not further demarcated in the text.

2.1. Social Media Platforms

This section reviews the existing academic work in the field of social media by providing basic definitions of the concept and explaining different categories and functionalities of existing platforms. Finally, an overview of the existing studies over social networks as the most popular social media platform is provided with a focus on the currently largest social network - Facebook.

2.1.1. Definitions and History

The term social media refers to "a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0 and allow the creation and exchange of user-generated content" (Kaplan and Haenlein 2010, pp. 61). As such, the interpretation of the above definition can further be expanded by explaining the two related terms, commonly used in the same connotation – Web 2.0 and User-Generated Content (UGC).

Although the term Web 2.0 was initially coined by DiNucci (2009, pp. 32) in a vision article describing the future of the Web, it is commonly related to Tim O'Reilly's definition presented in his article "What Is Web 2.0?" (O'Reilly 2007, pp. 17-37) where he explains the software design patterns which support this new concept. The main contribution of Web 2.0 are not new technologies but the new usage patterns instead, i.e. rather than being just passive consumers, users become active participants by sharing information, experiences and opinions with each other on social media platforms (Berthon et al. 2007, pp. 39-48). As such, Web 2.0 can be perceived as the technological platform for social media, facilitating (1) flexible Web design, (2) responsive user interfaces, and (3) creation of new applications, by reusing existing ones and combining data from different sources, but also as ideological platform supporting (4) collaborative content creation, (5) establishment of social networks of people, and (6) collaboration leading towards gathering of collective intelligence (Murugesan 2007, pp. 34-41).

The outcome of the collaborative content creation of the end-users on Web 2.0 platforms is referred to as User-Generated Content. It can be defined as "[…] i) content made publicly available over the Internet, ii) which reflects a certain amount of creative effort, and iii) which is created outside of professional routines and practices" (OECD 2007, pp. 9). Depending on the platform, it can occur in various forms, from textual content, through images, videos and musical content, to virtual goods (OECD 2007). Therefore, UGC can be seen as a result of different ways of social media usage.

While the concept of social media might be related to the launch of the first online discussion system - Usenet, in 1979 (Lueg and Fisher 2003), the social media as we know it today begun with the creation of the first social network (SN), SixDegrees.com (Cassidy 2006, pp. 50). Today social media incorporates numerous platforms which provide different functionalities as presented in the following section.

2.1.2. Categorization and Functionalities

With the growing number and offered variety of services provided by social media platforms, attempts have been made to define the similarities and differences by providing a categorization scheme. According to Kaplan and Haenlein (2010, pp. 59-68), social media platforms can be distinguished as belonging to one of the following six categories:

- *Collaborative projects*, which enable the joint creation of content and can further be divided into wikis and social bookmarking applications;
- *Blogs and microblogs*, which display time-stamped content, usually managed by one person with the possibility of interaction with others;
- *Content communities*, which allow for sharing of media content without the requirement for profile creation;
- *Social networking sites*, which enable users to create profiles, establish "friendship" with other users, and exchange information with them;
- *Virtual game worlds*, that replicate a three-dimensional environment and require their users to behave according to strict rules of the game; and
- *Virtual social worlds*, where users appear as avatars and are free to choose their behavior by living a virtual life similar to their real life.

Similarly, Constantinides and Fountain (2008, pp. 231-244) use the term *content aggregators*, to refer to *bookmarking applications* as a form of *collaborative projects* and they add *forums* as a separate social media platform used for exchange of ideas and information.

Apart from the categorization based on existing theories and offered services, social media platforms have been studied from the perspective of their functionalities. Kietzmann et al. (2011, pp. 241-251) propose the following

building blocks: identity, presence, relationship, reputation, groups, conversation, and sharing. The descriptions of the functionalities and their implications are detailed on Figure 3.

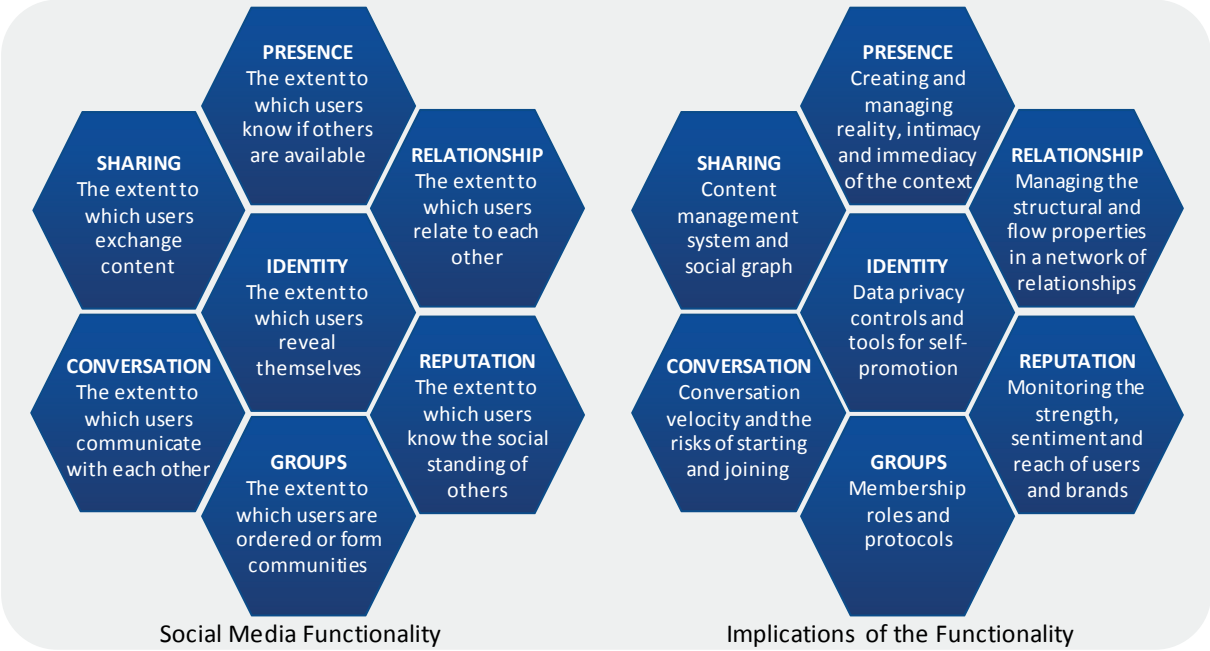

Figure 3: The seven functional blocks of social media and their implications (Kietzmann et al. 2011, pp. 241-251)

It should be noted that not all functionalities are present in each social media platform. For example, the core of the SN Facebook is the relationship functionality, followed by conversation, identity, presence and reputation (Kietzmann et al. 2011, pp. 241-251).

Despite the great number and variety of social media applications, SNs remain on the leading position, becoming a daily routine for millions of users (Cassidy 2006, pp. 50). The following section provides more details on social networks by introducing the concept and reviewing the previous academic work.

2.1.3. Social Networks as Largest Social Media Platform

A social network 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, pp. 210) 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 (Richter et al.2011, pp. 89-103).

The major leap happened with Facebook in early 2004 (Cassidy 2006, pp. 50). 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 955 million active users[16] and the most visited web page[17]. With such large numbers of users and activities, and a documented loss of consumer trust in traditional advertising (Clemons et al. 2007, pp. 267-276), 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[18].

SNs and Facebook have been studied from different perspectives (Richter et al.2011, pp. 89-103; Wilson et al. 2012, pp. 203-220), such as:

- characteristics of the users (e.g., Gjoka et al. 2008, pp. 31-36; Hargittai 2007, pp. 276-297; Karl et al. 2007, pp. 11-31; Ryan and Xenos 2011, pp. 1658-1664);
- usage patterns (e.g., Golder et al. 2007, pp. 41-66; Hsu et al. 2011, pp. 473-476; Lampe et al. 2006, pp. 167-170; Quinn et al. 2011, pp. 266-272),
- usage motivations (e.g., Joinson 2008, pp. 1027-1036; Krasnova et al. 2008, pp. 2124-2135; Raacke and Bonds-Raacke 2008, pp. 169-174),
- identity management and self-presentation (e.g., DiMicco and Millen 2007, pp. 383–386; Labrecque et al. 2011, pp. 37-50; Zhao et al. 2008, pp. 1816–1836),
- social interactions (e.g., Backstrom et al. 2011; Kostakos and Venkatanathan 2010, pp. 587-594; Nazir et al. 2008, pp. 43-56), and

16 Facebook Statistics. http://newsroom.fb.com/content/default.aspx?NewsAreaId=22. Accessed 2012-06-11

17 Alexa: Top Sites. http://www.alexa.com/topsites. Accessed 2012-09-19

18 Facebook drives US social network ad spending past $3 billion in 2011. http://www.emarketer.com/Article.aspx?R=1008180. Accessed 2012-06-11

- privacy and information disclosure (e.g., Brandtzaeg et al. 2010, pp. 1006-1030; Debatin et al. 2009, pp. 83-108; Krasnova et al. 2009, pp. 39-62).

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 interactions." (Richter et al. 2011, pp. 97) Similarly, Weston (2008) argues that SNs can also help find talent, build brand awareness, find new customers, and help conduct brand intelligence and market research. It is the business-to-customer (B2C) interactions that are in the focus of this thesis and they can be established through creation of online brand communities on social media platforms and attracting customers to join the brand related communication within these communities.

2.2. Brand Communities

This section reviews the existing academic work in the field of brand communities by providing basic definitions of the concept and explaining differences between the consumer and marketer-generated communities. In addition, the concept of brand engagement is introduced with a focus on the consequences of engagement in brand communities.

2.2.1. Definitions

In the era of computer-mediated communication, the concept of community grew from customary, familial, emotional and rural community (Tonnies 1887) to a larger and non-geographically bounded group of individuals with common purpose or identity (Wilson 1990). As such, community can be defined as "a network of social relations marked by mutuality and emotional bonds" (Bender 1978, pp. 145), which complies with the interpretation from the SN perspective (Oliver 1988, pp. 623–645).

Participation in online SNs was found to have a mediating effect between individuals and society in the virtual world (Wasserman and Faust 1994). As such, SNs represent a natural technological platform for marketing, providing access to a large number of users, grouped in non-geographically bound communities, based on a structured set of social relationships among admirers of a brand. This new form of communities is commonly referred to as (virtual) brand communities (Muniz and O'Guinn 2001, pp. 412-432).

Muniz and O'Guinn (2001, pp. 412-432) argue that brand communities should be characterized with the following core components:

- *shared consciousness*, as a common way of thinking beyond shared attitudes or perceived similarity, and a feeling of belonging (Weber 1978);
- *rituals and traditions*, which preserve the history, culture, and conventions of the community (Douglas and Ishwerwood 1979), manifested through certain behavioral norms and values (Marshall 1994); and
- *a sense of moral responsibility*, as a feeling of duty and commitment to the community as a whole and to its individual members, resulting in collective actions.

The above definition was further expanded by McAlexander et al. (2002, pp. 38-54) by placing the customer on the central position and pointing out to the previously recognized importance of branded possessions, i.e. products (Holbrook and Hirschman 1982, pp. 132-140) and marketing agents (Doney and Cannon 1997, pp. 35-51) for the customers. The resulting model maintains the brand customer relation proposed in the traditional model, as well as the customer-customer relation, proposed by Muniz and O'Guinn (2001, pp. 412-432), and is illustrated on Figure 4.

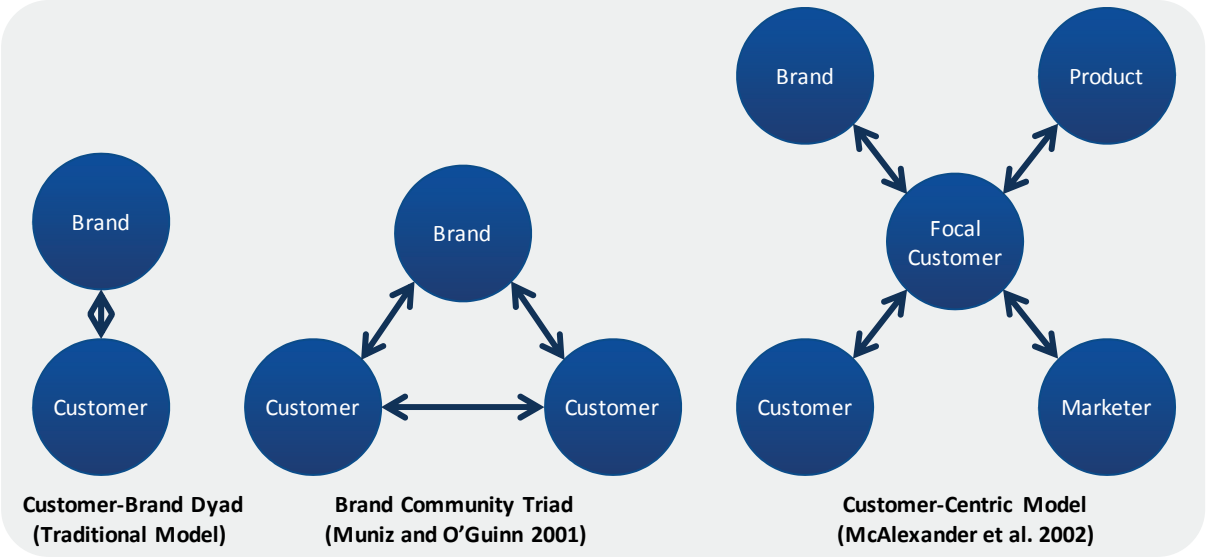

Figure 4: Key relationships in brand communities (McAlexander et al. 2002, pp.38-54)

Brand communities were found to be a successful tool for increasing sales (Adjei at al. 2010, pp. 634-653). In addition, they offer a network of

relationships with the brand and with other consumers (Quinn and Devasagayam 2005, pp. 101-114). Within this network, consumers can exchange their opinions about the brand or a particular product, thus engaging in a form of word-of-mouth marketing (WOM) and influencing each other through this communication (McAlexander et al. 2002, pp. 38-54). As such, brand communities have the potential of improving the relationships between individual consumers, as well as among the consumers and the brand (Sicilia and Palazon 2008, pp. 255-270). In addition, the relation and attitude towards the brand were found to depend fundamentally on the social interactions between brand community members (Fuller et al. 2008, pp. 608-619).

There are many benefits of managing a brand community for the companies. Participation in brand communities influences member perceptions and actions (Muniz and Schau 2005, pp. 737–747). Customers who belong to brand communities engage in the WOM communication, thus serving as brand advocates (McAlexander et al. 2002, pp. 38-54). In addition, according to Berry (1983, pp. 25-28), they are more forgiving of product failures and less likely to switch brands. Thus, brand community participation should result in an increased level of consumer trust and loyalty (Casalo et al. 2007, pp. 775-792).

From a marketing perspective, trust represents a key factor for establishing successful and long-term relationships (Dwyer et al. 1987, pp. 11-27), while loyalty, as one of the central concepts related to relationship marketing (de Ruyter et al. 1998, pp. 436-453), supports company success and sustainability over time (Flavian et al. 2006, pp. 363-375). Therefore, increasing the trust and loyalty should ultimately lead towards positive consumers' attitude, as a WOM objective, and attachment to the brand and the company (Hallowell 1996, pp. 27-42; McAlexander et al. 2002, pp. 38-54). In addition, previous studies showed that WOM has twofold effect: the volume of UGC increases the brand awareness (Godes and Mayzlin 2004, pp. 545-560), while the valence influences the brand attitude (Liu 2006, pp. 74-89). Furthermore, Ulusu (2010) argues that (1) members of brand communities on social media platforms are interested in receiving brand announcements on their profile pages, (2) feel as a part of the brand communities they have joined, (3) they accept the friendship request of the brand pages, and (4) value the opinion of their friends about a brand.

Rich body of research on brand communities already exists varying from luxury goods communities, such as cars (Muniz and O'Guinn 2001, pp. 412-432), games (Cova et al. 2007, pp. 313-329) and computers (Muniz and Schau 2007, pp. 35-50) to convenience products (Cova and Pace 2006, pp. 1087-1105). Still,

due to the market-place transformation caused by social media platforms, Marketing Science Institute (2008) suggests reassessment of the existing approaches, in order to appropriately address the newly faced challenges.

2.2.2. Classification of Brand Communities

Similarly to the variety of definitions, there is also a variety of categorizations of the brand communities in the existing literature. One of the possibilities is to use the community creator as a factor, thus distinguishing between the consumer generated brand communities, i.e. non-commercial communities, and those created by the marketers, commercial communities (Leimeister et al. 2006, pp. 277–298).

Non-commercial communities or consumer communities (Thorbjornsen et al. 2002, pp. 17-34) are built and managed in a volunteer manner by enthusiastic consumers who are eager to establish relationship with other consumers in order to exchange brand related information (Shang et al. 2006, pp. 398-418). Consumer communities are found to have a greater influence and are perceived as more credible than commercial ones (Bickart and Schindler 2001, pp. 31-40). Still, they might also represent a threat for the company and brand image due to the possibility of creation of negative content by unsatisfied or malicious consumers (Maclaran and Catterall 2002, pp. 319-326). Examples of successful consumer communities on social media already exist, such as the communities of Coca-Cola[19] and Pringles[20] on Facebook that have achieved a great success measured by the number of community members.

In contrast, commercial brand communities are initiated and funded by companies in order to engage in marketing communication by building relationships with their current and potential consumers (McWilliam 2000, pp. 43-54). By listening to the conversation within the brand community, companies can obtain insights about the perception of their products, but also gather ideas for new products and services (Leimeister et al. 2006, pp. 277–298). Growing popularity of social media resulted in creation of numerous commercial brand communities on Web 2.0 platforms. Disney, Red Bull or Victoria's Secret are just some of the existing examples which, in addition to fostering communication with their members, undertake other marketing actions such as offering gift cards and coupons, or event promotions.

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[19] Coca-Cola Facebook Page. http://www.facebook.com/cocacola. Accessed 2012-09-19

[20] Pringles Facebook Page. http://www.facebook.com/Pringles. Accessed 2012-09-19

Both types of brand communities are considered useful as marketing tools, since in terms of community commitment, satisfaction and future intention in brand community participation, no differences were found to exist between their members (Sung et al. 2010, pp. 5).

2.2.3. Consumer/Customer Engagement in Brand Communities

The change in the dynamics of marketing interchange between companies and consumers as introduced by SNs has placed a focus on the non-transactional customer behavior. In this new marketing era the terms engagement and participation became the central constructs used to describe the nature of participants' specific interactions and/or interactive experiences (Brodie et al. 2011, pp. 252-271; Kietzmann et al. 2011, pp. 241-251).

One of the early definitions of engagement within brand communities refers to it as “consumer’s intrinsic motivation to interact and cooperate with community members” (Algesheimer et al. 2005, pp. 21). Since then, the term has been increasingly used in the marketing literature and different, context-depended definitions were provided. While certain interpretations focus on the cognitive and emotional aspects of engagement (Bowden 2009, pp. 63-74), others refer to the concept of engagement primarily as a specific activity type or pattern (Van Doorn et al. 2010, pp. 253-266). In an attempt to provide a definition which tackles all aspects of customer engagement in brand communities, Brodie et al. (2011, pp. 254) formulate the following:

“Consumer engagement in a virtual brand community involves specific interactive experiences between consumers and the brand, and/or other members of the community. Consumer engagement is a context-dependent, psychological state characterized by fluctuating intensity levels that occur within dynamic, iterative engagement processes. Consumer engagement is a multidimensional concept comprising cognitive, emotional, and/or behavioral dimensions, and plays a central role in the process of relational exchange where other relational concepts are engagement antecedents and/or consequences in iterative engagement processes within the brand community.”

Previous studies in the field of customer engagement focused mostly on the consequences of the engagement, including previously mentioned concepts of trust (Hollebeek 2011, pp. 785-807), satisfaction (Bowden 2009, pp. 63-74), commitment and emotional attachment (Chan and Li 2010, pp. 1033-1040), empowerment (Cova and Pace 2006, pp. 1087-1105; Fuller et al. 2009, pp. 71-

102), consumer value (Schau et al. 2009, pp. 30-51), and loyalty (Andersen 2005, pp. 39-51; Casalo et al. 2007, pp. 775-792). Thus, understanding the influencing factors which could increase the level of engagement is a worthy goal which would ultimately lead towards improvement of company's profitability (Kumar et al. 2010, pp. 297-310).

In addition, brand related communication between the members of the brand community results in UGC which, apart from increasing the brand awareness and attitude (Godes and Mayzlin 2004, pp. 545-560; Liu 2006, pp. 74-89) could lead towards product development (Bolotaeva and Cata 2010; Richter et al.2011, pp. 89-103). Thus extracting meaningful information from the large amount of UGC on social media platforms could provide additional value to the companies.

2.3. User-Generated Content

This section reviews the existing academic work in the field of UGC with a focus on knowledge extraction from the large amount of unstructured text on social media platforms. In the continuation, basic definition and classification of the UGC will be introduced, followed by a review of existing work in the field of text mining of UGC.

2.3.1. Definition and Classification

As already mentioned in Section 2.1: "Social Media Platforms", the term User-Generated Content refers to the publicly available content, created by individuals on online platforms. As such, the form of UGC varies, depending on the platform where it was created. An overview of different types and corresponding examples of UGC, as defined by OECD (2007), is provided in Table I.

Table I: Classification of user-generated content across social media platforms (OECD 2007)

Type of Content	Description	Examples
Text, fiction and poetry	Original writings or expanding other texts, novels, poems, etc.	Fanfiction.net, Quizilla.com, Writely, etc.

Type of Content	Description	Examples
Photos and images	Digital photographs taken by users and posted online; photos or images created or modified by users.	Photos posted on sites such as Flickr; photo blogging, etc.
Music and audio	Recording and/or editing personal audio content, publishing or distributing.	Audio mash-ups, remixes, home-recorded music on band websites or MySpace pages, podcasting.
Video and film	Recording and/or editing video content and posting it (e.g., content remixes, homemade content, etc.).	Movie trailer remixes; lip-synching videos; video blogs and videocasting; posting home videos. Sites include YouTube and Google Video; Current TV.
Citizen journalism	Journalistic reporting on events by citizens who write news stories, blog posts, and post them online.	Sites such as OhmyNews, GlobalVoices, etc.; photos and videos of newsworthy events; blog posts reporting an event; cooperative efforts such as CNN Exchange.
Educational content	Content created in schools, universities, or for educational use.	Syllabus-sharing sites such as H20; Wikibooks, MIT's OpenCourseWare.
Mobile content	Content created on mobile phones or other wireless devices such as text messaging, photos and videos.	Videos and photos of public events or natural catastrophes that traditional media may not be able to cover; text messages for political rallying.
Virtual content	Content created within the context of an online virtual environment or integrated into it. User created games.	Virtual goods that can be developed and sold on Second Life including clothes, houses, artwork, etc.

As the number of available sources and the amount of UGC on online platforms increase, individuals and companies interested in gathering knowledge through monitoring of the conversation on social media platforms need to rely on the tools capable of automatic document analysis and classification. This is generally known as text mining and will be described in the following section.

2.3.2. Extracting Knowledge from User-Generated Content

Related to the understanding of the conversation within the social media platforms is the field of text mining. The existing text mining algorithms mostly focus on (1) opinion mining and sentiment analysis, or (2) trend detection. An overview on both research streams is provided in the continuation.

2.3.2.1. Opinion Mining and Sentiment Analysis

Related to the understanding of the conversation within the social media platforms is the field of opinion mining and sentiment analysis. The term opinion mining was coined by Dave et al. (2003, pp. 519-528) to describe a tool that would "process a set of search results for a given item, generating a list of product attributes (quality, features, etc.) and aggregating opinions about each of them (poor, mixed, good)". Approximately at the same time the term sentiment was used in reference to the automatic analysis of evaluative text and the tracking of predictive judgments (Das and Chen 2007, pp. 1375-1388), thus the two disciplines are interconnected.

Early studies in opinion mining focus on the interpretation of narrative points of view in the text. The growth of Web 2.0 with its content sharing platforms revealed the opportunity for further expansion in the direction of machine processing and machine learning algorithms (Baloglu and Aktas 2010, pp. 77-84). Today there are numerous papers investigating different research problems and opportunities derived from opinion mining and sentiment analysis (Pang and Lee 2008, pp. 1-135).

The importance of opinion mining for social media marketing has already been recognized (Nasukawa and Yi 2003, pp. 70-77). Opinion mining allows companies to conduct analyses of UGC to determine how the population perceives a given brand, product or feature, i.e. for market analysis and rumour detection. This resulted in research on analyzing long structured text discussions from blog posts (Kaltenbrunner et al. 2007, pp. 57-66; Liu et al. 2007, pp. 607-614), as well as utilizing such communication for the prediction of user behaviour, sales, stock market activity, etc. (Adar et al. 2007, pp. 161-170; De Choudhury et al. 2008, pp. 55-60; Liu et al. 2007, pp. 607-614).

The change in social media towards short commentary, as introduced by SNs Twitter[21] or Facebook, results in a significant difference in the comment structure and language that may affect the accuracy of opinion mining

[21] Twitter. https://twitter.com/. Accessed 2012-07-18

techniques (Simm et al. 2010, pp. 552-557). This has motivated research into text analysis and application of the opinion mining techniques to social media in order to understand the activities and identify the specific issues with the relevance to the language used in this noisy environment.

Recent studies focus on applying the opinion mining techniques on short comments from the SN Twitter to investigate the value of tweets as online word-of-mouth (Jansen and Zhang 2009, pp. 2169-2188), possibilities for movie revenue prediction (Asur and Huberman 2010, pp. 492-499) and opportunities for television broadcasters (Diakopoulos and Shamma 2010, pp. 1195-1198), perform sentiment analysis (Bermingham and Smeaton 2010, pp. 1833-1836), enable web-based intelligence retrieval and decision-making (Cheong and Lee 2009, pp. 1-8), etc. Yet, opinion mining and sentiment analysis over the UGC on Facebook still represents a challenge.

In addition to extracting opinions and sentiment from UGC, providing an aggregated view on topics that are being referred to within the UGC on social media platforms represents an additional field of study, commonly known as trend detection. The following section reviews the concept and provides examples on the existing work in this field.

2.3.2.2. Trend Detection

Trend Detection (TD) is a research field that has been of interest for information retrieval and text mining applications for a long time. A recent variation of the concept appeared under the notion of Emerging Trend Detection (ETD), which according to Kontostathis et al. (2003, pp. 2) is characterized by a "[…] topic area that is growing in interest and utility over time." A system performing detection of emerging trends uses a document corpus as input and identifies topics that are new or show significant growth in importance within the corpus. In turn, ETD builds up on the results from the work of the Topic Detection and Tracking (TDT) initiative (Allan 2002).

TDT explores the possibility and required mechanisms for topic extraction from a time-stamped corpus of documents, such as news channels. The task of topic extraction is divided into five separate research problems: (1) story segmentation, (2) first story detection, (3) cluster detection, (5) tracking, and (5) story link detection (Allan 2002). Each of these elements has caused a separate thread of research within the field of information retrieval. The results of the TDT project have further supported the development of various automated systems for detection and tracking of emerging topics through time, i.e. trend detection and monitoring (Kontostathis et al. 2003, pp. 185-224).

Social media as a source of information has recently attracted the attention of these research communities. However, most of the efforts related to trend detection over social media focus on analysis of the long structured text discussions from blog posts, such as the work of Bansal and Koudas (2007, pp. 1410-1413). By comparison, detection of trends in UGC on social networks is still in its infancy.

The change brought about by social media towards short commentary, as introduced by SNs, such as Twitter and Facebook, resulted in a significant difference in the comment structure and language, imposing additional challenges to the existing text mining techniques (Simm et al. 2010, pp. 552–557). For that reason, the majority of the previous research over the content shared on SNs focus on understanding the users, activities, opportunities and challenges of these platforms. Furthermore, these studies mostly apply the text mining techniques on comments from Twitter, as already explained in the previous section. However, the number of studies regarding Facebook is still relatively limited (Richter et al.2011, pp. 89-103).

The efforts in the direction of trend detection on Twitter lead also to the creation of several commercial tools for monitoring trends. Apart from the official tool offered by Twitter, i.e. Twitter Search[22], there are many other platforms which provide similar features, such as, Trendsmap[23], WhatTheTrend[24], etc. In addition, research oriented platforms are being created to provide scholars with the tools that would enable investigation of the trend generation phenomena (Goorha and Ungar 2010, pp. 57-64; Mathioudakis and Koudas 2010, pp. 1155-1158).

From the research perspective, there have been two major streams: (1) adapting the existing and providing new algorithms for text mining, and (2) understanding the phenomena of trend occurrence and spreading. The work belonging to the first stream includes examples such as improved algorithms for first story detection based on locality-sensitive hashing (Petrovic et al. 2010, pp. 181-189), overcoming the problems of document summarization through definition of a notion of hybrid documents in the traditional term-frequency approach (Sharifi et al. 2010, pp. 49-56), usage of Latent Dirichlet Allocation (LDA) method for topic identification (Ramage et al. 2010, pp. 130-

22 Twitter Search. http://search.twitter.com/. Accessed 2012-08-10

23 Trendsmap. http://trendsmap.com/. Accessed 2012-08-10

24 WhatTheTrend. http://www.whatthetrend.com/. Accessed 2012-08-10

137), trend detection via keyword clustering (Mathioudakis and Koudas 2010, pp. 1155-1158), news recommendation (Phelan et al. 2009, pp. 385-388), etc.

In the direction of the second stream, Asur and Huberman (2010, pp. 492-499) have provided a theoretical basis for the formation, persistence and decay of trends. Becker et al. (2011, pp. 291–300) have recognized the value of Twitter as a source of real-time event content. Naaman et al. (2011, pp. 902-918) reveal the value of tweets for gathering information for, and about, a local community. Kwak et al. (2010, pp. 591-600) investigate different characteristics of Twitter trends in terms of the number of replies, mentions, retweets, and "regular" tweets that appear in the set of tweets for each trending term. Sakaki et al. (2010, pp. 851–860) study social, spatial, and temporal characteristics of earthquake-related tweets and Diakopoulos et al. (2009, pp. 115-122) analyze tweets corresponding to the large-scale media events to improve reasoning, visualization and analytics.

Content created through a consumer-to-consumer communication on social media platforms can be seen as an extension of the traditional concept of WOM communication. It should be noted that there is an important difference in these two constructs: while UGC refers to content created by the users, WOM refers to content which is transmitted by the users. For example, a post created on Facebook brand page is a UGC. Once it is shared, it becomes WOM communication. An overview of previous research on WOM is provided in continuation.

2.4. Word-of-Mouth Marketing

This section reviews the existing academic work in the field of word-of-mouth communication and its value for marketing. In the continuation, basic definition will be provided, followed by a review of previous studies in the field of WOM on online platforms, commonly referred to online or electronic WOM. Finally, the related concept of viral marketing as a special form of electronic WOM marketing will be introduced.

2.4.1. Definitions

According to one of the oldest definitions, WOM can be seen as a process of informal, brand or product related communication within a social network of consumers (Brooks 1957, pp. 154-161). Traditional (offline) WOM is usually conducted through oral, in-person communication between two parties, the "communicator", as a person who transmits the message, and the "receiver",

as the recipient of the message. In this dialog a non-commercial message in a form of opinion or recommendation regarding a certain product or a service is exchanged (Arndt 1967, pp. 291-295).

WOM communication was found to be a powerful tool for marketing which influences consumer's attitudes towards existing products and leads to adoption of new products (Katz and Lazarsfeld 1955). This is due to the fact that WOM messages which originate from close friends or family are perceived as more objective and credible compared to marketing messages communicated by the companies (Brooks 1957, pp. 154-161; Katz and Lazarsfeld 1955). In addition, the concept of trust is further expanded to opinions of other customers which might not belong to a person's immediate social network, such as those written in the form of online reviews (Duana et al. 2008, pp. 1007-1016). As such, WOM is frequently used by individuals as a source of brand or product related information (Buttle 1998, pp. 241-254), playing a significant role for purchase decision making (Richins and Root-Shaffer 1988, pp. 32-36), pre-usage attitude (Herr et al. 1991, pp. 454-462) and post-usage evaluation of products (Westbrook 1987, pp. 258-270).

Previous studies in the field mostly focused on the consequences of WOM, in particular on the impact of the negative WOM (e.g., Richins 1983, pp. 68-78; Singh 1990, pp. 1-15). In addition, motives for engagement were of interest for scholars and marketers, pointing to altruism, product involvement and self-enhancement as the most common reasons for participation (Sundram et al. 1998, pp. 527–531). In addition, it was shown that the frequency and intensity of WOM communications depend on the type of products and markets, characteristics of the social network, as well as the personality and culture of involved individuals (Buttle 1998, pp. 241-254). Finally, WOM was examined from the perspective of its relevance for different industry domains, where food and home appliances were found to be the category which is influenced the most (Katz and Lazarsfeld 1955). In addition, WOM was found to be influential factor for service industry, such as automotive or medical services (Singh 1990, pp. 1-15).

Despite the recognized value and a relatively long history, WOM marketing is relatively underused by the companies as a part of their marketing campaigns (Buttle 1998, pp. 241-254; Gremler et al. 2001, pp. 41-59). This is mostly due to the common belief and concern that WOM communication cannot be controlled and that positive WOM can only be achieved through positive product experiences (Gremler et al. 2001, pp. 41-59).

Recent development of the Web 2.0 Internet technologies lead to expansion of the brand related communication lead by the consumers over the social media platforms (Dellarocas 2003, pp. 1407-1424). This new form of WOM, known as online WOM (oWOM) or electronic WOM (eWOM) has attracted the attention of scholars and practitioners who tried to explain the nature of this new phenomenon and recognize its potentials. This lead to further studies as described in the following section.

2.4.2. Electronic Word-of-Mouth

Electronic WOM can be defined "as any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet" (Hennig-Thurau et al. 2004, pp. 39). As such, eWOM differs from its traditional form by increasing the speed and reach of WOM communication through social media platforms which support "many-to-many communication" (Hoffman and Novak 1996, pp. 50-68).

eWOM communication can occur on different technological platforms which support different forms of communication and result in various forms of UGC, depending on the communication scope (one-to-one, one-to-many and many-to-many) and the level of interactivity of the underlying platform (synchronous vs. asynchronous communication) (Litvin et al. 2008, pp. 458-468).

The changes brought about with this new form of WOM communication introduce new challenges and opportunities for marketers. Increasing the scale of the WOM communication as a result of the low cost of access and information exchange might potentially change the market dynamics. Further, the potential introduced by the broader scope and complexity of the used technological platforms in turn allow for greater control over the communication and the resulting UGC. Finally, anonymity of the participants might lead to intentional malicious and out-of-context messages (Dellarocas 2003, pp. 1407-1424). As a result of these changes, the number of consumers exposed to the content created by opinion leaders on online platforms will continuously increase (Hennig-Thurau et al. 2004, pp. 38-52).

The concept of eWOM was studied from the following perspectives: the effect of eWOM on sales (Godes and Mayzlin 2004, pp. 545-560), motivations for participation (Hennig-Thurau et al. 2004, pp. 38-52), eWOM in virtual communities (Kozinets et al. 2010, pp. 71-89), etc. In addition, opportunities for targeting traditional marketing objectives were investigated. In that

direction, Dellarocas (2003, pp. 1407-1424) argues that eWOM opens the possibility for brand building, customer relationship management, and product development. Similarly, Jansen and Zhang (2009, pp. 2169-2188) propose an extension of a traditional marketing model which illustrates the relation between the brand knowledge and customer purchase behavior to the social media domain. An illustration of the identified scope of the effect of eWOM in the specific marketing areas is given on Figure 5.

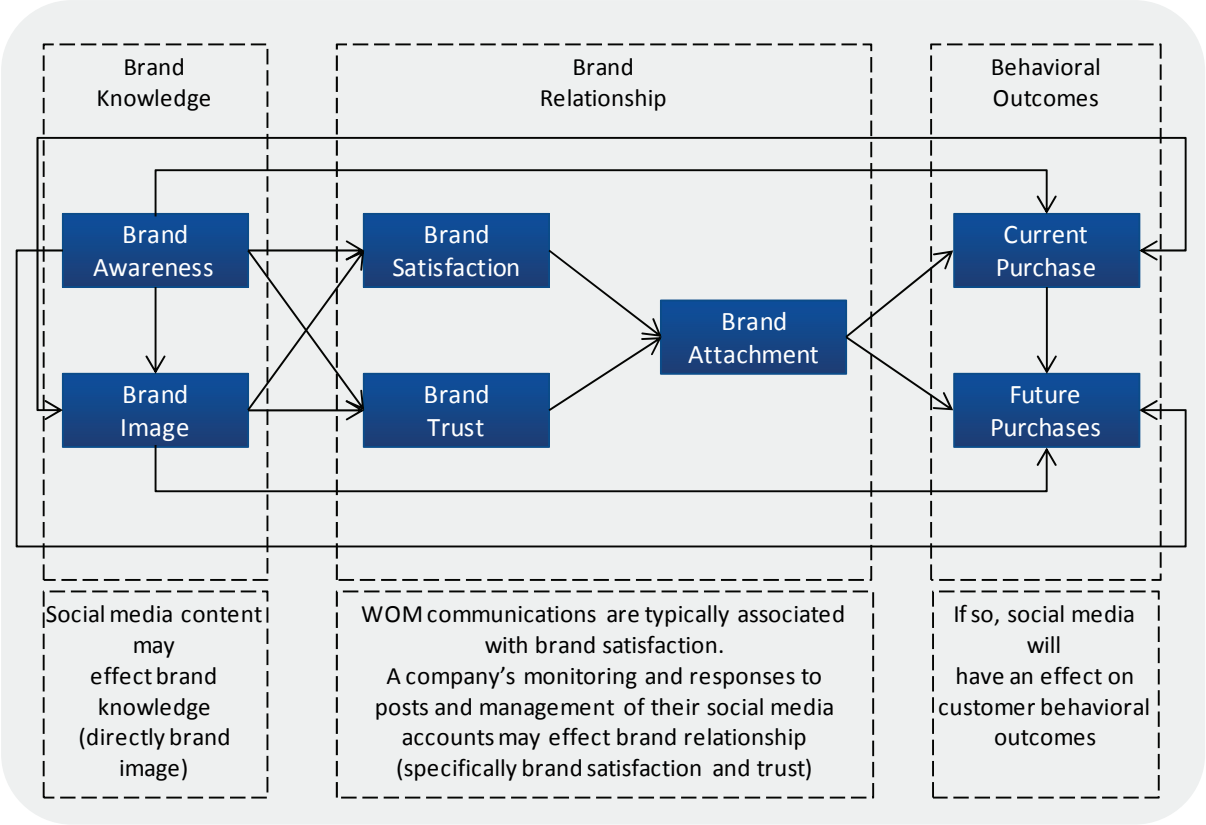

Figure 5: General model of branding components and relationship with social media (adopted and generalized for social media from Jansen and Zhang 2009, pp. 2169-2188)

It can be seen that content shared on social media platforms directly influences the brand knowledge thus having an influence over the brand image. Further, grand satisfaction is also related to WOM communication, while the trust and attachment can be controlled by appropriate actions. Thus careful creation of social media strategies which take in consideration the recognized relations could lead to the ultimate goal, i.e. increase in sales.

The concept of eWOM is used interchangeably with the term "viral marketing". A discussion on whether and how these two forms of consumer-driven brand related communication differ from each other is provided in continuation.

2.4.3. Viral Marketing

Viral marketing is a concept which appears in the literature under variety of names, such as word-of-mouse (Goldenberg et al. 2001, pp. 211–223), buzz marketing (Thomas 2004, pp. 64–72), stealth marketing (Kaikati and Kaikati 2004, pp. 6-22), and WOM marketing (Kozinets et al. 2010, pp. 71-89).

The term "viral marketing" was initially introduced in 1996 by a Harvard Business School faculty member, Jeffrey Rayport (Kaplan and Haenlein 2011, pp. 253-263), in his famous article "The Virus of Marketing"[25] in which he claims: "Every marketer aims to have a dramatic impact on thinking and behavior in a target market; every successful virus does exactly that." Since then, the term has been increasingly used in academic literature and among the marketing practitioners, and numerous definitions have been proposed, mostly focusing on making a distinction between the concepts of "viral marketing" and WOM marketing.

Viral marketing can be seen as a diffusion of information about the product and its adoption over existing social network platforms (Leskovec et al. 2006, pp. 228-237). Kaplan and Haenlein (2011, pp. 253-263) expand this definition by proposing that viral marketing is a form of eWOM where marketing messages related to a company, brand, or product are transmitted in an exponentially growing way, through the use of social media platforms. In turn, Kirby and Marsden (2006) argue that there is a difference between the viral marketing and eWOM such that viral marketing refers to marketing campaigns whose goal is creation of persuasive messages which are designed to be spread online, as opposed to WOM marketing which undertakes action with a goal of stimulating the consumers to talk positively about the company, product or a service.

Previous research in the field has tried to address the concept from several perspectives, such as the dynamics of viral marketing (Leskovec et al. 2006, pp. 228-237), motivations for message propagation (Phelps et al. 2004, pp. 333-348), knowledge sharing and influence (Subramani and Rajagopalan 2003, pp. 300-307), deriving guidelines for practitioners (Kaplan and Haenlein 2011, pp. 253-263), and identifying marketing strategy components, such as giving away products or services, providing effortless message sharing, supporting easy scaling, exploiting common motivations and behaviours, utilizing existing social

[25] The virus of marketing. Fast Company. http://www.fastcompany.com/27701/virus-marketing. Accessed 2012-08-17

media platforms and taking advantage of others' resources (Wilson 2000, pp.1-2). In addition, the relation of the concept to the WOM clearly indicates that findings from eWOM field of study, such as implications for marketing, can also be applied to viral marketing.

WOM communication and viral marketing as its specific form are at the core of a new form of marketing activities undertaken by companies on social media platforms. This new form of marketing is commonly known as social media marketing and will further be elaborated in the following section.

2.5. Social Media Marketing

This section reviews the existing work in the field of marketing on social media platforms by explaining the basic concepts and drivers for adoption, listing the identified challenges and opportunities and providing insights into the utilization guidelines derived from existing examples and theories. Finally, an overview of the state of the art in terms of effectiveness evaluation of social media marketing is provided.

2.5.1. Definitions and Drivers

Despite the popularity of the topic in both academia and practitioners circles, due to its novelty, at the time of writing of this thesis there is no established formal definition of the concept of SMM.

Mangold and Faulds (2009, pp. 357-365) point out that SMM is to be seen as hybrid element of the marketing mix which supports two forms of promotion: (1) traditional marketing promotion, as a part of the integrated marketing communications (IMC) which refers to the communication driven by the companies towards their customers, and (2) social promotion, which is unique for social media platforms and is embodied within the consumer to consumer communication. The second interpretation is adopted by most of the scholars, referring to SMM as a utilization of the existing social media platforms for increasing the brand awareness among consumers on online platforms through utilization of the word-of-mouth principles (Drury 2008, pp. 274–277; Ma et al. 2008, pp. 233-242).

Social media may play a key role in the future of marketing (e.g., Berthon et al. 2012, pp. 261-271; Harris and Rae 2009, pp. 24-31; Mangold and Faulds 2009, pp. 357-365); it may increase customers' engagement, and help to transform the traditional focus on control with a collaborative approach suitable for the

modern business environment. This statement could be supported by findings which showed that consumers are turning away from the traditional sources of advertising (Vollmer and Precourt 2008). In turn, social media becomes a preferred source of information regarding products and services, frequently used as a basis for purchase decision making (Harrison-Walker 2001, pp. 60-75).

An illustration of these changes, showing the factors that influence the purchase decision making on social media platforms, as proposed by Constantinides and Fountain (2008, pp. 231-44), is provided on Figure 6.

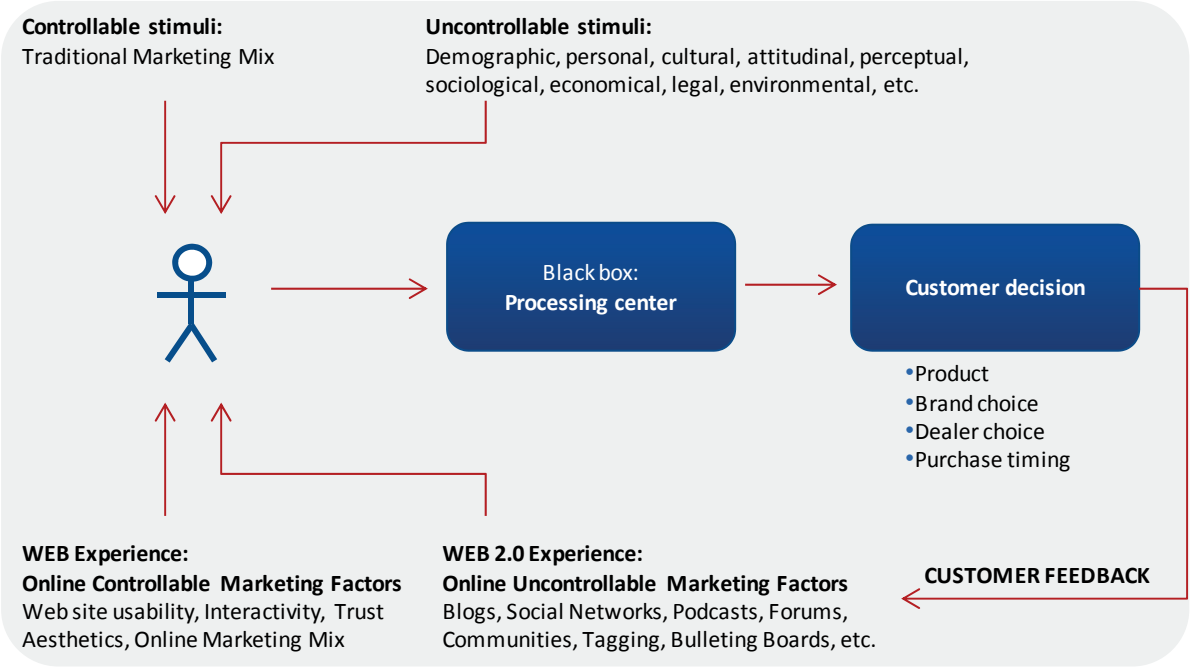

Figure 6: Factors affecting the buying decision-making process in a Web 2.0-mediated environment (Constantinides and Fountain 2008, pp. 231-44)

It can be seen that the challenges of SMM lie in the existence of numerous uncontrollable stimuli and factors resulting from the nature of social media platforms which cannot be controlled by the marketing strategies. As a result, the process of decision making still remains a "black box".

The main difference between the marketing on social media platforms and traditional marketing approach is that SMM cannot be fully controlled by strategies focused only on the content, frequency, timing, and medium of communications (Mangold and Faulds 2009, pp. 357-365). User participation as a main feature of the social media platforms 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). One approach towards

establishing a successful strategy, suitable for SMM is to start by identifying the challenges and opportunities of social media utilization (Kaplan and Haenlein 2010, pp. 59-68).

2.5.2. Challenges and Opportunities of Social Media

In order to provide insights to practitioners looking to use SNs to benefit their brands, previous studies in the field of SMM have focused on identifying the challenges of SMM, such as aggressive advertisement, lack of e-commerce abilities, legal issues and lack of brand control (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, pp. 24-31). 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, pp. 193-207).

Apart from the challenges, many opportunities have also been recognized, such as raising public awareness about the company, product development through community involvement and gathering experience for the future steps by analyzing the UGC (Bolotaeva and Cata 2010; Richter et al.2011, pp. 89-103). In addition, Drury (2008, pp. 274–277) recognizes the value of online marketing strategies such as social search and viral campaigns supported by social media platforms, and further points out to the increased Internet access via mobile devices, opening an additional possibility for mobile marketing. Finally, as Javitch (2008) advises, free SMM is a good alternative to the costly traditional marketing campaigns and he explains that getting involved on SNs also means protecting the business name.

2.5.3. Guidelines for Successful Social Media Utilization

Based on exploratory findings and practical examples, scholars have tried to generate guidelines for successful SMM. In general, guidelines that apply for online WOM, also apply to SMM: (1) sharing the control of the brand with consumers and (2) engaging them in an open, honest, and authentic dialog (Brown et al. 2007, pp. 2-20). Similarly, Mangold and Faulds (2009, pp. 357-365) recommend establishing a control by shaping the conversation through (1) usage of new or existing social media platforms, (2) integration of traditional and Internet-based promotional tools, (3) providing information and exclusivity, (4) supporting causes that are important to consumers and (5) utilizing the power of storytelling. Kaplan and Haenlein (2010, pp. 59-68) go

one step further by distinguishing between the guidelines for social media usage and those for being social, stressing out the importance of appropriate tone selection and honesty. In addition, similar to Mangold and Faulds (2009, pp. 357-365), they also recommend integration of marketing campaigns across traditional and social media.

In general, both scholar and practitioners recommend that companies need to build an engagement plan 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, pp. 245–250). Li (2007a) suggests (1) focusing on a conversation, (2) developing a close relationship with the brand through "friending" with social media pages and (3) finding out what interactions, content, and features will keep users coming back. This could be achieved by continuous and well defined measurement, fine-tuning and optimization (Meadows-Klue 2008, pp. 245–250). Similarly, Kozinets et al. (2010) argue that the first step towards understanding the conversation lies in the classification of different types of content. Also, they note that the communication is affected by the type of offered product or service. Still, as Richter et al. (2011, pp. 89-103) point out, 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 with the brand communities.

2.5.4. Effectiveness Evaluation of the Marketing Efforts

With the growing number of companies utilizing social media for marketing, the question of evaluation of marketing efforts emerged. Previous findings in the field are mostly based on case studies and can be divided into two main streams: (1) effectiveness evaluation of sponsored ads on social media platforms (Maurer and Wiegmann 2011, pp. 485 - 498), and (2) effectiveness evaluation of social campaigns (Dholakia and Durham 2010, pp. 26). The first stream does not differ from the concept of online advertisement and as such is not of interest for this thesis. Therefore, the discussion provided in continuation will be limited to the second stream which corresponds to the concept of SMM.

Effectiveness evaluation of SMM efforts is still in a relatively early stage of development. 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, pp. 94-99). Still, 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 (e.g., Hoffman and Fodor 2010, pp. 41-49; Murdough 2009, pp. 94-99).

In order to contribute in this direction, recently the focus of scholars turned to extending the existing marketing theories by applying empirical research. For example, Chu (2011, pp. 30-43) argues that there is a positive effect of the Facebook group participation over general attitude towards SMM. Jahn and Kunz (2012, pp. 344-361) explore the factors that could convert consumers into loyal fans, pointing out to the importance of fostering engagement by providing valuable content. In addition De Vries el al. (2012, pp. 83-91) try to examine the specific content features that would increase the level of engagement on Facebook brand pages. Finally, an attempt to evaluate the effectiveness of SMM showed that a carefully managed Facebook advertising campaign increased the sales (Dholakia and Durham 2010, pp. 26). Still, as Wilson et al. (2012, pp. 211) point out, “these few studies only begin to touch on ways in which Facebook can be used to connect with customers.”

2.6. Summary

This chapter provided a short overview of the existing academic work in the fields relevant for the study conducted as a part of this thesis. The fields that were reviewed include:

- Social media and social networks as the largest social media platform;
- Brand communities on social media platforms and the benefits of customer engagement in these communities for marketing;
- User-generated content as an outcome of brand community participation, with the focus on knowledge extraction from content shared by users on social media platforms;
- Word-of-mouth marketing as a process of creation and sharing of brand related user-generated content with a focus on the electronic word-of-mouth conveyed on social media platforms and its specific form, viral marketing as a word-of-mouth with exponential speed of sharing;
- Social media marketing, as a new form of marketing based on the brand community creation on social media platforms which allows consumers to engage in word-of-mouth communication, resulting in user generated

content, which can serve as a source of knowledge and ideas for the marketers.

Based on the provided review, a clear gap in the literature was identified, (1) a lack of understanding of the concept of social media marketing and (2) a lack of empirical studies which would confirm the assumed benefits of its utilization. In addition, (3) there are no established methods for evaluation of the effectiveness of the undertaken marketing efforts.

This thesis addresses the above listed points by conducting empirical studies with a goal of increasing the understanding of the social media utilization for marketing purposes and proposing a framework for effectiveness evaluation. The proposed framework can be used by marketing practitioners as a tool for continuous monitoring of activities and conversations, providing results which can further be used as input for strategy adjustment.

Summary of Main Points

- Identified research gap in the domain of social media marketing:
  - Lack of understanding of the concept and its utilization (Richter et al. 2011, pp. 89-103);
  - Lack of empirical studies to confirm the value of undertaken actions (Wilson et al. 2012, p. 203-220);
  - Lack of established methods for effectiveness evaluation (Dubach Spiegler 2011; Murdough 2009, pp. 94-99);
- Domains of interest for academia and practitioners:
  - Building an engagement plan should start by focusing on the ongoing conversation (Li 2007a).
  - Brand image monitoring can be achieved through monitoring trends (Kasper and Kett 2011, pp. 662-669).
  - Understanding the user characteristics offers important insights for optimization of the SMM efforts (Fidgeon 2011).
  - The value of SMM can be measured through the amount and richness of the interactions (Parent et al. 2011, pp. 219-229).
  - Companies should find out which content, and features will keep users coming back (De Vries et al. 2012, pp. 83-91).
  - Addressing ROI from the engagement perspective provides opportunity to develop strategies that fit with marketing objectives, such as brand engagement, WOM and brand awareness (Hoffman and Fodor 2010, pp. 41-49).

3. Facebook as a Platform for Social Media Marketing

The selection of Facebook as an underlying platform for this thesis was based on the reasoning that with 955 million monthly active users[26], Facebook is currently the largest and fastest growing social network[27]. In addition, Facebook is considered by the companies as the most attractive social media platform to be used for marketing, in particular for B2C businesses (Hubspot 2012). This is further confirmed in a recent industry survey conducted by Social Media Examiner (Stelzner 2012) showing that 92% of marketers are using Facebook for their marketing communication and 72% are planning to increase their activities on Facebook. Figure 7 illustrates the popularity of Facebook compared to other social media platforms.

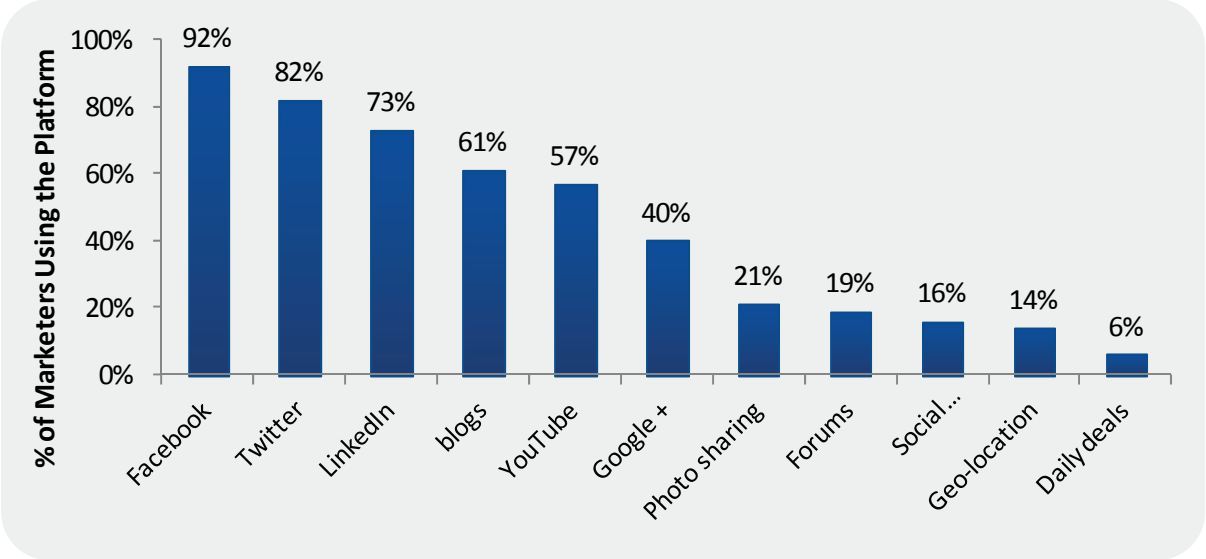

Figure 7: Usage of social media platforms for marketing purposes (Stelzner 2012)

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[26] Facebook Statistics. http://newsroom.fb.com/content/default.aspx?NewsAreaId=22. Accessed 2012-06-11

[27] Alexa: Top Sites. http://www.alexa.com/topsites. Accessed 2012-09-19

3.1. Basic Terminology

A brief introduction of the basic Facebook terminology provided in this section will further be used as a basis for explanation of the main concepts relevant for utilizing Facebook for marketing purposes. The following list contains the explanation of the most important concepts based on the official Facebook definitions[28]:

- *Profile* is a space dedicated to each Facebook user for creation and customization of personal profile including photos, videos, personal information and more. It can be configured as *public* or *private*.
- *Page* is a space on Facebook dedicated to brands, businesses, organizations, and entertainers. It can be *followed* or *liked* by the Facebook users, thus creating a subscription to all updates made on the page's wall (see Figure 8 for an illustration).
- *Timeline* is the central part of the *profile page* which shows all user's updates and activities in reverse chronological order.
- *Wall* is the older version of the *timeline* representing a place where the user can publish updates and where his friends can post direct updates to the user.
- *Friend* is a person to whom a social connection has been established and with whom a user can share content and updates. Friending with other Facebook users by sending or receiving *friend requests* results in a *list of friends* visible on a profile page.
- *News Feed* is a list of status updates on the user's home page showing the activities from user's *friends* and followed *Facebook pages*. It can be configured to show *most recent* or the *top stories*.
- *Top Stories* are those stories published since the last visit to the page which are ranked as important based on the relationship to the person who posted the story, number of comments and likes it got, the type of a story, etc.
- *Ticker* appears on the right side of the home page and is updated with friends' activities in real-time.

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28 Facebook Glossary. http://www.facebook.com/help/glossary/. Accessed 2012-08-08

- *Like* is the cover action of Facebook. It is available in several formats: (1) as a link under any content created on Facebook, where the interaction with it results in as an update on user's *wall* or as a *(2) button* available on pages for joining the community of page followers. Liking can also be done over any online content integrated with the Facebook social plugins without leaving the web page.

In the following section, several additional definitions are provided which explain the marketing possibilities on Facebook.

3.2. Marketing Possibilities on Facebook

Apart from providing services to individuals, Facebook also offers the possibility to marketers and business owners for professional promotion. This can be achieved through several features integrated in the platform, which enable companies for undertake different forms of marketing activities:

- *Ads* appear on the right side of the Facebook page and they resemble any other online ad that is not specific to social networks. 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) click-through rate (CTR), i.e. how often customers interact with them.

- *Social Plugins* allow Facebook users to log in to websites, mobile applications, etc. using their Facebook accounts, thus providing immediate access to their personal information and lists of friends. In addition, they provide the possibility to like or share any online content, without the need to leave the web page. Finally, social plugins support targeted marketing by providing the possibility to send specific content to optimal audience through the Graph Targeting feature[29].

- *Apps* provide access to a large number of users, serving the advertisement information in combination with the entertainment content, with the most popular category being the Facebook games. A recent trend relevant for companies goes into direction of creating

[29] Facebook Opens up Open Graph Targeting Options. http://www.insidefacebook.com/2012/02/15/facebook-opens-up-open-graph-targeting-options/. Accessed 2012-08-08

platforms for online shopping on Facebook, i.e. F-commerce applications[30].

- *Brand Pages* are pages created by the companies which offer the opportunity for a more active engagement, both on the side of the brand owner as well as the customer, who can become member of a company's Facebook page and engage in a direct communication with the company.

- *Sponsored Stories* are similar to ads such that they promote social connections people make with the brand page, app or event. Since individuals are influenced by the opinions of their friends, this feature provides the possibility to "boost" these stories so that they can be seen by larger number of Facebook users.

Of the above listed features, Facebook brand pages are (1) free to create and use, (2) provide the possibility to share and receive the richest form of content, and (3) offer largest number of engagement possibilities with the community members. As such, brand pages are selected as a platform to be investigated within the research presented in this thesis.

3.3. Facebook Brand Pages

The concept of *Facebook brand pages* was introduced by Facebook in November 2007[31]. The goal was to enable Facebook users to connect with their favorite brands by providing "distinct, customized profiles designed for businesses, bands, celebrities and more to represent themselves on Facebook"[31]. In addition, brand pages can also be created by enthusiastic individuals, and those pages will further be denoted as *related brand pages*.

Related pages are sometimes even adopted and supported by the companies, such as in the case of Coca-Cola which was initially created by two big fans of the beverage, and being supported as an official page it soon became the largest brand community on Facebook, with approximately 46 millions of fans at the time of writing.

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[30] F-Commerce: The Arrival of the Facebook Consumer. http://www.clickz.com/clickz/column/2056609/-commerce-arrival-facebook-consumer. Accessed 2012-08-08

[31] Facebook Ads. https://blog.facebook.com/blog.php?post=6972252130. Accessed 2012-08-08

An illustration of a Facebook brand page, showing the profile image and the timeline with a post from the moderator (left), recent posts by the fans (right) and number of fans (30 millions) is given on Figure 8.

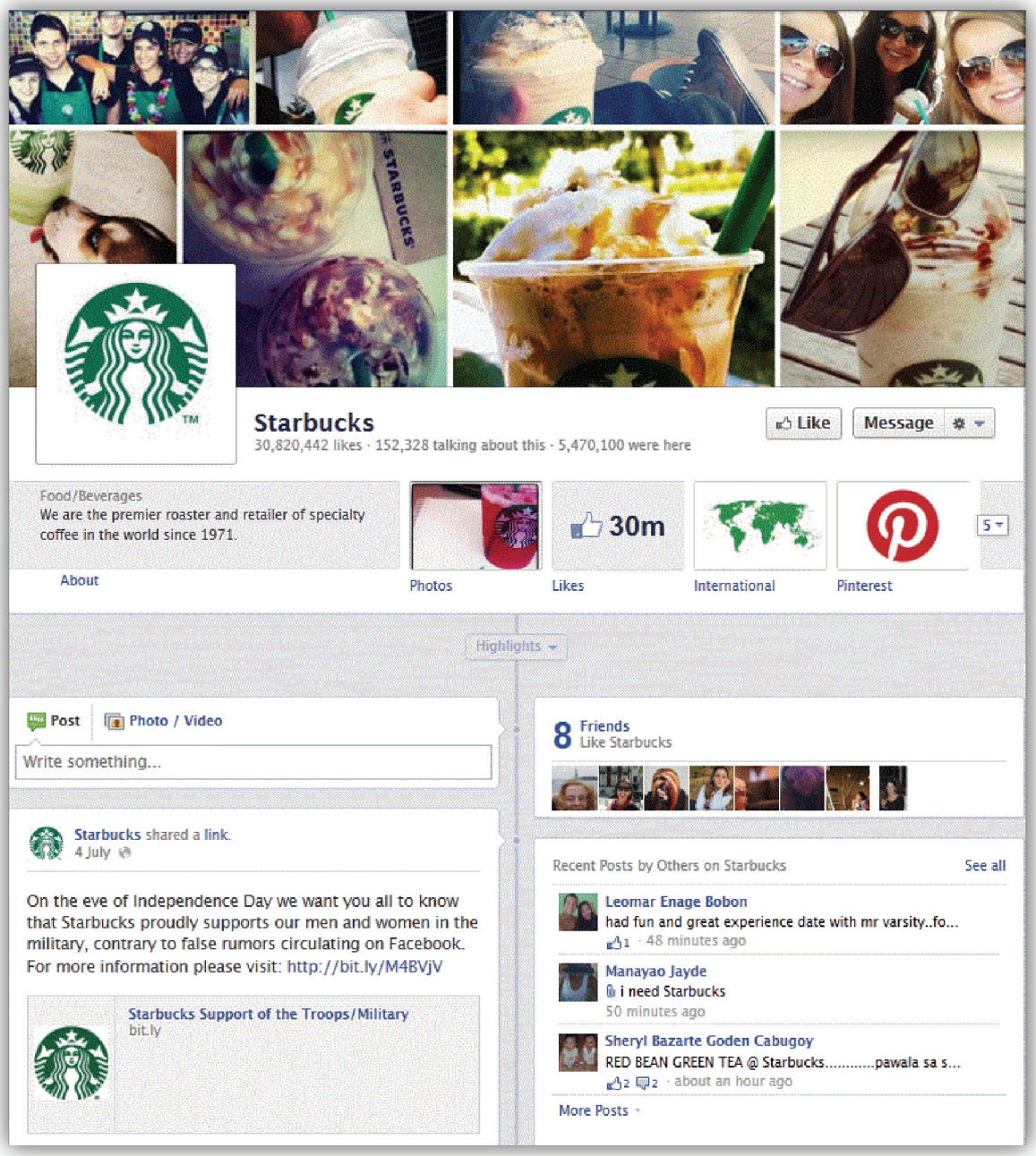

Figure 8: Example of a Facebook brand page showing the page wall, number of fans, a post from the moderator and the recent posts from the page fans

In order to define the terminology, a description of the concepts used in this thesis will be provided, based on the previously introduced basic definitions from Facebook.

The content shared on brand pages is referred to as *posts*. Posts may vary in *content* but also in *media type* (*status*, *photo*, *link* or *video*), and appear on the central part of the brand page, i.e. the *wall* or *timeline*. Each brand page might have one or more administrators responsible for creation and deletion of posts, i.e. the *page moderator(s)*. A brand page can have any number of members, who joined the page by pressing the *Like* button. In the continuation they will be referred to as *fans*.

Within a Facebook brand page, fans can engage by: (1) *posting* content on the wall (depending on the *communication policy* set by the company), (2) *commenting* on the existing post, (3) indicating interest in a post by pressing the "Like" button, i.e. *liking*, and (4) *sharing* the post on their profile wall. Each of these actions increases the reach of the content by creating a visible trace, i.e. a *story* on the user's wall, thus making it visible to all of his friends. Fans who posted more than once will further be referred to as *returning fans*.

According to "best practice" manual for marketing on Facebook[32], companies should establish a brand presence on Facebook by building and promoting brand pages. These should further be used to deepen the relationship with the consumers by engaging and connecting with the Facebook fans through social and interactive strategies. Finally, in order to evaluate the marketing efforts and gain insights into the target audience, a continuous and real-time analysis of the activities and responses is required. The first step towards evaluation is data collection, described in the following section.

3.4. Available Data Sources on Facebook

There are two available sources of data describing the activities undertaken by fans on a Facebook brand page: (1) *Facebook Insights*[33], and (2) *Facebook Graph API*[34].

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32 Best Practice Guide: Marketing on Facebook. http://ads.ak.facebook.com/ads/FacebookAds/Best_Practice_Guide_042811_10.pdf. Accessed 2012-08-08

33 Facebook Insights. http://www.facebook.com/help/?page=168695703191089. Accessed 2012-08-08

34 Facebook Graph API. http://developers.facebook.com/docs/reference/api/. Accessed 2012-06-11

3.4.1. 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 a daily level about the users, such as demographics (gender, age, cities, language, etc.) and number of fans, as well as some details on the interaction with 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 and can be exported for further examination. Figure 9 illustrates the level of details provided on the platform.

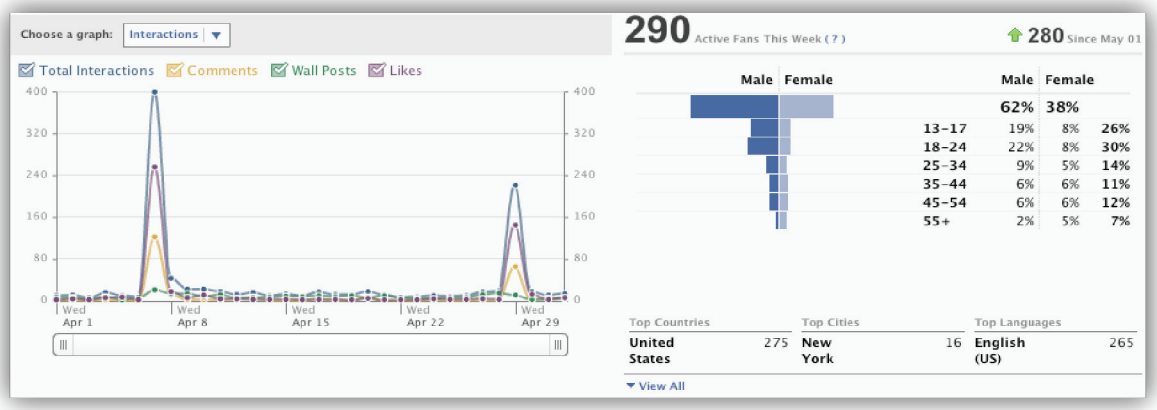

Figure 9: Facebook Insights screen showing interactions and demographics information about the brand page fans

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 *impressions*, i.e. post views, is defined as the number of times people have viewed a post, though this can only be counted as the number of times the post appeared on someone's 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. However, many of the shortcomings of the Facebook Insights tool can be worked around by using the Facebook Graph API described below.

3.4.2. Facebook Graph API

The 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, such as friends, events, etc.

Every object in the graph is characterized with a unique identification number which can be used to access its data. Thus to obtain the information about a Facebook brand page, a *Page* object can be returned based on the following query:

```
https://graph.facebook.com/<PAGE_ID>
```

where *<PAGE_ID>* refers to the Facebook identification of the brand page. Alternatively, pages can also be accessed by their usernames.

The result received after sending the *Page* query is formatted as a JSON array and contains the main object fields, such as (1) page name and id, (2) Facebook category, (3) number of fans at the moment ("likes"), (4) number of fans "talking about" the page, etc. As an illustration, the answer obtained for the Starbucks' brand page is given in Listing 1.

Listing 1: Example listing of a *Page* object returned by the Facebook Graph API

```
{
   "id": "22092443056",
   "name": "Starbucks",
   "picture":"http://profile.ak.fbcdn.net/[…]",
   "link": "http://www.facebook.com/Starbucks",
   "likes": 30821077,
   "cover": {
      "cover_id": "10150906911398057",
      "source": "http://a1.sphotos.ak.fbcdn.net/[…]",
      "offset_y": 0
   },
   "category": "Food/beverages",
   "is_published": true,
   "website": "www.starbucks.com ",
   "username": "Starbucks",
   "founded": "1971 in Seattle's Pike Place Market",
   "company_overview": "Starbucks has an unusually […]",
   "mission": "Our mission: to inspire and nurture […]",
   "products": "Coffee",
   "description": "Our story began in 1971 […]",
   "about": "We are the premier roaster and retailer […]",
   "were_here_count": 16,
   "talking_about_count": 147384
}
```

While the *Page* object can be publicly accessed, to collect information about its connections an authorization token is required. The Graph API uses OAuth 2.0 for authorization which generates a token further used as an additional parameter of the query. The details of the process for obtaining and usage of the authorization tokens are provided in the dedicated Facebook Developers page[35] and will not be elaborated further.

The *Feed* connection of the *Page* 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 fan, (4) likes (number and fan details), (5) comments, (6) shares, (7) application used for posting, (8) creation time and (9) time of last interaction. An illustration of the response obtained for the *Feed* connection is provided in Appendix XI.

The details of the interaction with the API and the exact format of the obtained responses are documented at the Facebook Graph API site and will not be elaborated here further.

The main advantage of the Graph API compared to Facebook Insights is that 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 competitors' 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 completeness and accuracy, the collection of the data should be performed on a daily basis. This is in particular important since the *Page* object itself can only be obtained for the given moment when the query is issued. Thus, the measures such as number of fans and number of fans "talking about" the brand page, which are considered as important for effectiveness evaluation, cannot be collected retroactively. In addition, for those objects from the graph that can be collected retroactively, the proposed approach ensures independence from potentially changing Facebook policies or system failures which might result in incompleteness of the data.

The approach described in this section was employed to gather the data used as a basis for the analysis conducted as a part of this thesis. Characteristics of

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35 Facebook Authentication. http://developers.facebook.com/docs/authentication/. Accessed 2012-08-08

the obtained datasets as well as the small variations in terms of the used Facebook Graph API features will be separately described for each of the conducted studies presented in the following chapters.

3.5. Social Media Strategies

The data collected from the sources described in the previous section can be used to establish a process of measurement of the effectiveness of the social media efforts. The obtained insights should further be used to undertake actions which could lead towards improved social media strategies, thus also to successful utilization of Facebook for marketing.

3.5.1. Measurement and Monitoring of Marketing Efforts

Provided by the platform for free, Facebook Insights is used by the companies as the main tool for observation of the effect of their efforts by tracking the activities on their brand pages (Dubach Spiegler 2011). In addition, several commercial tools perform similar analysis based on the data collected thorough the Graph API, such as AllFacebookStats[36], enabling companies to compare their performance with those of other brand pages of interest.

Apart from tracking the number of fans and engagement, companies also utilize tools which perform measurement and monitoring of the communication over multiple social media platforms. A numerous tools which provide automatic monitoring are already available[37]. Although these two terms are often used interchangeably, it should be distinguished that measurement is focused on benchmarking and tracking the efforts over time which might result in a list of actionable insights. In turn, monitoring represents real-time listening of the conversation and providing timely response to prevent negative publicity. As such, both of these processes are important and should be integrated in the social media strategy.

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36 AllFacebookStats. http://www.allfacebookstats.com/. Accessed 2012-08-08

37 A Wiki of Social Media Monitoring Solutions. http://wiki.kenburbary.com/. Accessed 2012-08-06

3.5.2. Deriving Guidelines

Based on the obtained results of the measurements and existing examples, both scholars and practitioners are trying to derive guidelines for SMM utilization.

The approach of both groups differs in a way that scholars mostly give general recommendations based on existing theories, as presented in the Chapter 2: "Related Work". As an illustration, some of the previous studies suggest providing social media platforms for communication, and integration of different marketing channels into a coherent marketing mix for optimal performance (Mangold and Faulds 2009, pp. 357-365). Further, models have been developed which enable creation of strategies for monitoring, understanding, and responding to different social media activities (Kietzmann et al. 2011, pp. 241-251). Finally, recommendations have been given to avoid over-commercialization and foster social interactions and dialog instead (Harris and Rae 2009, pp. 24-31).

In turn, practitioners mostly approach the problem from the perspective of defining precise communication and posting policies which are not general but are specific for Facebook as a chosen social media platform. The large number of existing guidelines can be used as an estimate of the importance of this question for the companies. Still, the drawback of these social media strategies is that they are mostly based on few examples or personal experiences and as such they lack a formal empirical evaluation and confirmation.

To contribute in the direction of increasing the understanding about the SMM on Facebook by providing insights to both, academia and practitioners, the continuation of this thesis presents five studies conducted over different aspects of utilization of Facebook brand pages: (1) user generated content on (a) brand pages and (b) public profile pages, (2) users and usage of brand pages, (3) brand engagement and (4) relation between the brand engagement, loyalty, WOM communication and community growth. Based on the obtained results, each of the presented studies derives implications for marketing practitioners. Finally, based on the presented studies, an evaluation framework consisted of specific steps and methods is proposed which should enable continuous measuring and monitoring of the interactions and the results of the undertaken actions, thus providing a possibility to the companies for adjustment of their social media strategies in accordance to the specific characteristics of their brand communities.

3.6. Summary

This section provides a brief introduction into the SN Facebook as a platform for SMM. Based on the basic Facebook concepts, a terminology and definitions were provided which are relevant for social media marketing and Facebook brand pages as a platform selected for further investigation. In addition, the two main sources of data were described which are used within the studies presented in the following chapters. Finally, a brief discussion was given on the state of the art in regard to the existing social media strategies from the perspective of measurement and monitoring practices and deriving guidelines based on the obtained results.

This discussion supports the recognized gap and the goal of this thesis to improve the current status by providing insights to academia and tools and guidelines to the practitioners.

Summary of Main Findings

- 92% of marketers are using Facebook for their marketing communication and 72% are planning to increase their activities on Facebook.
- Facebook supports the following marketing possibilities: (1) *Ads*, (2) *Social Plugins*, (3) *Apps*, (4) *Brand Pages* and (5) *Sponsored Stories*.
- *Facebook brand pages* are *pages* created by the companies with a purpose to engage in a brand-related dialog and are:
  - Free to create and use,
  - Provide the possibility to share and receive the richest form of content, and
  - Offer largest number of engagement possibilities with the community members.
- The content shared on brand pages is referred to as *posts*.
- A company representative responsible for creation and deletion of posts is the *page moderator(s)*.
- A brand page can have any number of members referred to as *fans*.
- Fans can engage by: (1) *posting*, (2) *commenting*, (3) *liking*, and (4) *sharing*.
- There are two available sources of data from Facebook brand pages:
  - *Facebook Insights* – provides daily aggregated data and is limited to own pages only;
  - *Facebook Graph API* – provides detailed data for any brand page but does not provide demographics data.

4. User Generated Content on Facebook Brand Pages

Analysis of the UGC was already recognized as an important element of social media strategies. According to Kozinets et al. (2010, pp. 71-89), classification of different types of content should be the first step towards understanding the customer conversation on social media platforms. In addition, the communication might be affected by the type of offered product or service (Kozinets et al. 2010, pp. 71-89). Similarly, Li (2007a) recommends that companies need to build a communication plan 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. One step towards achieving this goal is to focus on the consumer-driven conversation.

The study presented in this chapter addresses the research questions RQ1: "What are the topics of conversation?", RQ2: "What are the intentions for participation in brand communities on social media?" and RQ3: "Which emotions are shared within the UGC and how?" presented in Chapter 1.2.1.1: "User-Generated Content on Social Media Platforms". It explains the topics referred to within the UGC on Facebook brand pages and reveals intentions for participation in Facebook brand communities.

This study was originally published as: "Understanding Social Media Marketing: A Case Study on Topics, Categories and Sentiment on a Facebook Brand Page" (Pletikosa Cvijikj and Michahelles 2011d, pp. 175-182). In addition, an extended version of the previously referenced publication appeared under the title: "Understanding the User Generated Content and Interactions on a Facebook Brand Page" (Pletikosa Cvijikj and Michahelles 2013). Thus this section contains excerpts from the previously referenced publications which are not further demarcated in the text.

4.1. Introduction

User-generated content (UGC), defined as "the sum of all ways in which people make use of social media" (Kaplan and Haenlein 2010, pp. 61), was recognized as an important outcome of the customer engagement on social media platforms. UGC can be seen as an instrument which allows customers to express themselves and communicate with each other on online platforms (Boyd and Ellison 2008, pp. 210-230). As such, for the companies it offers to the possibility to listen to the customer-driven brand-related communication which is similar to the WOM communication (Kozinets et al. 2010, pp. 71-89; Muniz and Schau 2007, pp. 35-50). Thus UGC on social media platforms has a potential to influence the brand awareness (Godes and Mayzlin 2004, pp. 545-560) and brand attitude (Liu 2006, pp. 74-89), ultimately leading towards increase in the sales (Adjei et al. 2010, pp. 634-653).

The volume of creation and consumption of UGC is constantly climbing. A report published by eMarketer[38] estimates that the number of UGC consumers in US will reach 154.8 million, while the number of UGC creators will reach 114.5 million. In addition, most of the UGC is predicted to originate from the participation on SNs (105.3 million), thus turning SNs into an appealing platform for marketers.

UGC takes different forms on different social media platforms (Smith et al. 2012, pp. 102-113), varying from videos on YouTube[39], short textual messages (as those shared on the micro-blogging platform Twitter), Facebook posts with different media types, or even consumer-produced reviews and advertisements (Ertimur and Gilly 2012, pp. 115-130; Muniz and Schau 2007, pp. 35-50). In addition, differences were found to exist from the content perspective, such as the brand centrality role in the UGC, targeting the communication towards the marketers or responding to marketer's actions, and the level of expressed sentiment (Smith et al. 2012, pp. 102-113). As such, understanding the structure and differences among the UGC created on different social media platforms is potentially important for the marketers interested in utilization of social media platforms for co-creation of their brands.

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38 A Spotlight on UGC Participants. http://www.emarketer.com/Article.aspx?R=1006914. Accessed 2012-07-18

39 YouTube. http://www.youtube.com/. Accessed 2012-07-18

This chapter provides threefold contribution towards understanding the UGC on Facebook brand pages. The initial focus of the study is placed on identification of the topics referred to within the posts created by page fans. Further, categories of posts are identified and described, serving as an indication for intentions for participation on Facebook brand pages. Finally, an overview of the valence and format of sentiment shared by the fans within the posts is provided.

The continuation of this chapter is structured as follows. Section 2 describes the used methodology, while Section 3 presents the results of the evaluation. Section 4 discusses the findings and proposes implications for SMM practitioners. Finally, Section 5 provides a summary, discussion on the limitations of this study and proposes ideas for future work.

4.2. Method

4.2.1. Dataset

Collection of the data for this study was performed using the customized Java tool, based on the Facebook Graph API, as described in Chapter 3.4: “Available Data Sources on Facebook”.

The obtained dataset consists of posts shared on the ok.- Facebook brand page (see Chapter1.4.2: “Fast-Moving Consumer Goods as a Product Category” for details). The data collection was employed from March 2010 to March 2011. Within the selected period, 759 posts shared on the ok.- brand page were obtained. Of those, 134 posts were published by the page moderator and the remaining 625 by the fans. Further, 3 fan posts were removed due to the difficulty in recognizing the used language and an additional 11 after being labelled as spam, leaving 611 posts created by the page fans for qualitative analysis described in the continuation.

4.2.2. Data Analysis

The ok.- brand, whose Facebook brand page was used as a source of data for this study, is present only in the German speaking part of the Switzerland. Although German is the official language in this part of the Switzerland, in daily conversation a dialect is used, know as Swiss German, which significantly differs from the High German. In addition, there are large variations within different parts of Switzerland. For example, German translation of the English word “breakfast” is “Frühstück”, while the in the Swiss German dialect, forms

such as “Z'Morge” or “Morgenässe” are used instead. Furthermore, there are no standardized rules for the written form, which means that the same word can be written differently. This applies even for very simple words such as personal pronouns, e.g. the English pronoun for first-person singular. i.e. “I”, can be written in Swiss German as “i”, “ig”, “ich” (High German), or “isch”. This introduces challenges to the existing automatic opinion mining techniques based on the usage of a labelled training corpus to learn the relevant classification function based on the feature extraction and similarity calculation. In case when the same feature differs in form and writing, the precision of the obtained results reduces.

To overcome the described challenges, the manual analysis based on the action-object approach for post classification was applied (Zhang and Jansen 2008, pp. 414–433). Action-object approach suggests two basic components in the interaction between the user and a system, action - representing a specific expression of the user, and object – being a self-contained information object which serves as the recipient of the action. As such, this approach was found to be suitable for manual analysis of the UGC content shared on social media platforms (Jansen and Zhang 2009, pp. 2169-2188).

In order to perform the action-object classification, the coding development strategy, as proposed by Glaser and Strauss (1967), was followed. The idea of this approach is to build new theories based on the manual investigation of the data through coding and grouping of the similar codes, known also as grounded theory method. Thus, the process consisted of three steps:

- **Coding Strategy Development**: Initially, a manual coding scheme was created to define the classification rules, e.g. “content which contains a mention of the brand will be coded as ‘brand’”, “content which contains a mention of the individual product will be coded as ‘product’”, post that appear in form of question will be coded as “*information inquiry*”, etc.

  Expected topics, i.e. “objects” which were of interest for this study included references to the brand, product, specific feature and competitors. For the “action” coding, the following post forms were of interest: (1) asking a question, (2) expressing sentiment, (3) praise and (4) complaints.

  Apart from these, manual investigation of the content revealed additional topics and actions, which were added post-hoc to the coding scheme.

- **Coding**: Using the defined coding strategy, each of the posts was assigned one or more codes to identify the key concepts contained within the content, e.g., the post:

  "mi favorit: ok.- Branchli - wenn gits die im Jumbo-Pack?"(original)

  "my favourite: ok.- chocolate bar - when will there be a jumbo pack?" (English translation)

  was coded as "*product*", "*positive affect*", "*information inquiry*", "*suggestion*" and "*package*".

- **Integrating**: Based on the coding results, grouping of similar codes was performed in order to identify the action-object pairs and groups of related codes, by assigning "group descriptors".

  For the previous example, the resulting group descriptors were: (1) '*Product: Affect: Positive*', (2) '*Sales: Availability: Launch Date: Information Inquiry*' and (3) '*Product: Feature: Package: Suggestion*'.

This approach captured the following aspects of the posts: (1) *topics* referred to within the posts, (2) intentions for participation, further denoted as *post categories*, and (3) *sentiment* present in the content.

4.3. Results

As already mentioned, content analysis revealed the (1) topics, (2) categories, and (3) sentiment contained within the posts. Results obtained for each of these aspects are detailed in the continuation.

4.3.1. Topics of Conversation

In order to understand the interests of the fans on a Facebook brand page, an analysis was performed to identify what is being talked about, i.e. to identify the topics of conversation. The obtained results identified seven major topic groups: (1) *Product* (318 posts, 52% of the total), (2) *Sales* (79, 13%), (3) *Brand* (46, 8%), (4) *Competitor* (26, 4%), (5) *Facebook Contest* (20, 3%), (6) *Company* (11, 2%) and (7) *Environment* (3, 0%).

The distribution of posts over topic groups is illustrated on Figure 10.

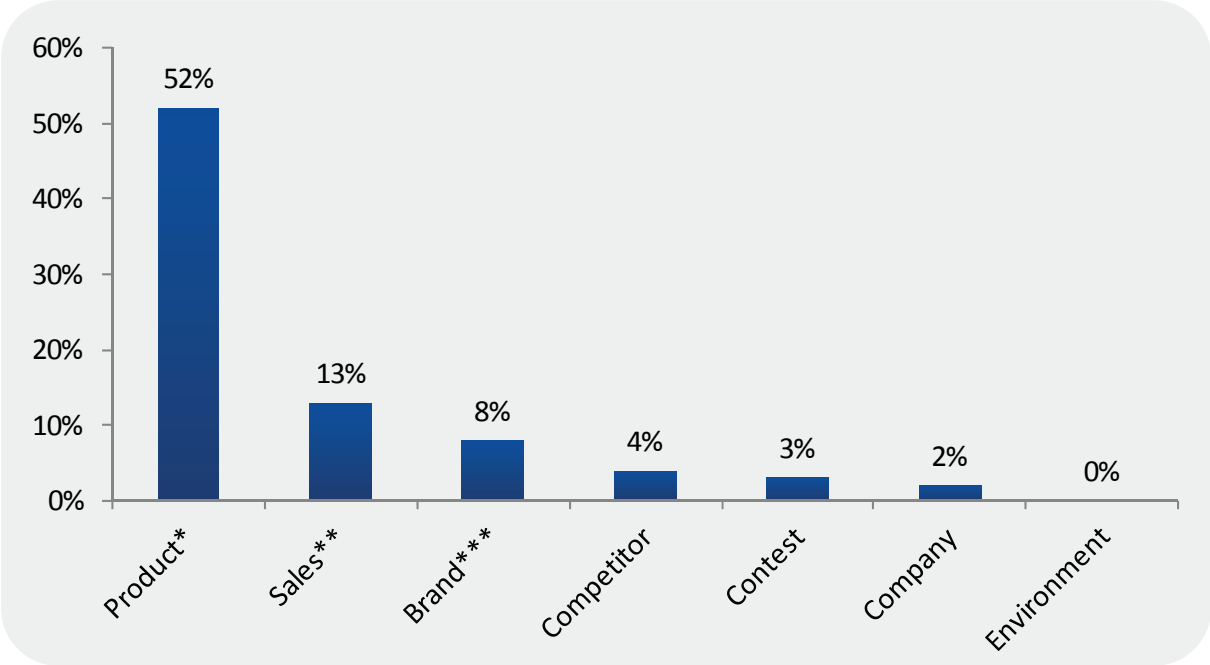

Figure 10: Main topic groups obtained through the analysis of the user generated content on a Facebook brand page (*p < 0.0001, **p < 0.005, ***p < 0.05)

To evaluate the differences in proportions of posts belonging to different topic groups, two-proportion Z-test for statistical analysis was applied by comparing each topic group with the "following" one with lower number of occurrences, For example. *Product* was compared to *Sales*, *Sales* to *Brand*, *Brand* to *Competitor*, etc.

The results of the statistical analysis showed that there is a significant difference ($Z = 14.54$, $p < 0.0001$) in the proportion of *Product* posts compared to the proportion of posts referring to *Sales*. Furthermore, the proportion of posts regarding *Sales* was found to be significantly larger ($Z = 3.02$, $p < 0.005$) compared to the proportion of *Brand* related posts, while the number of *Brand* mentions was significantly larger ($Z = 2.31$, $p < 0.05$) compared to the number of *Competitor* posts. Thus, *Product*, *Sales* and *Brand* topic groups are also larger compared to all of the topic groups with smaller number of mentions. For the remaining topic groups, no significant differences were found to exist.

The applied action-object approach provided the possibility to understand the content with a better granularity by dividing each topic group into more specific sub-topics. The obtained sub-topics and their distribution, relative to the topic group, are presented on Figure 11.

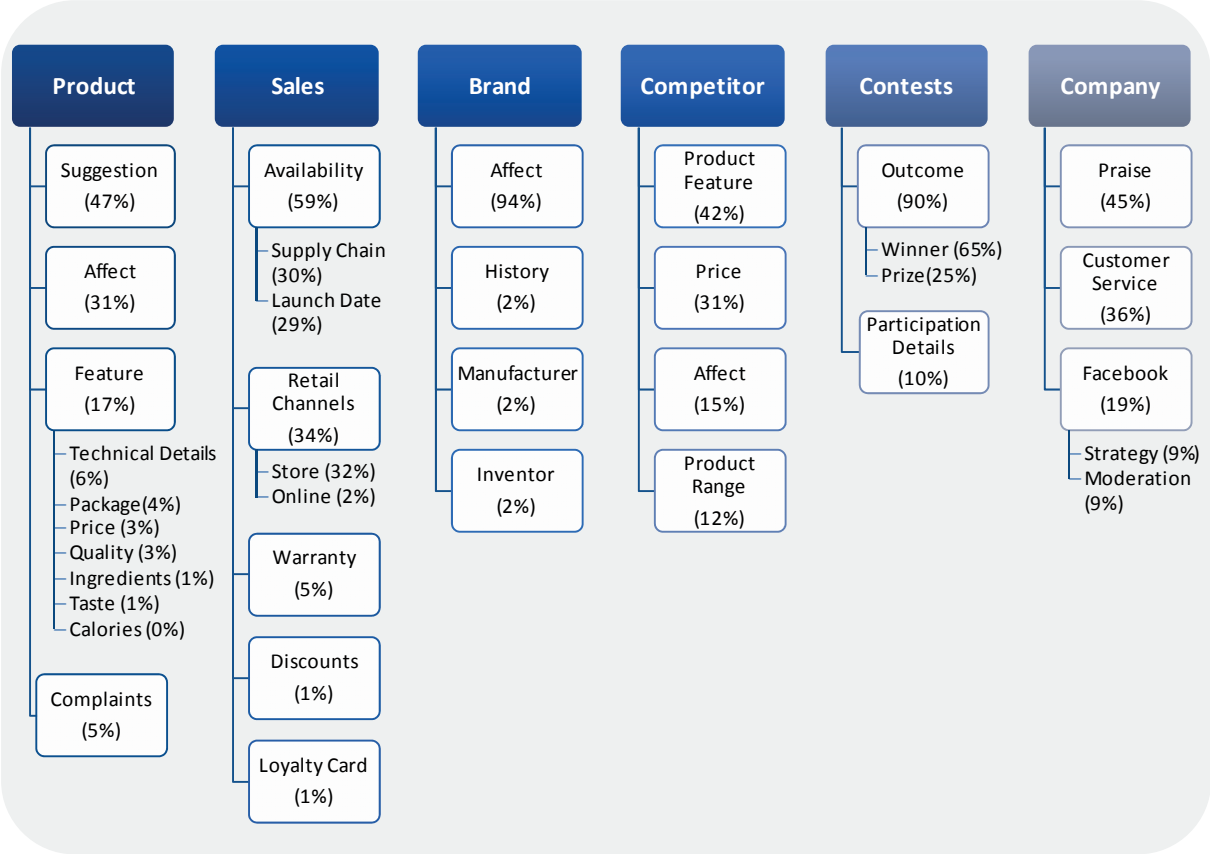

Figure 11: Extracted sub-topics belonging to each of the main topic groups

In the following text an explanation is provided for each of the topic groups. In addition, the most frequent subtopics are identified and their value from the marketing perspective is discussed.

4.3.1.1. Product

Product was found to be the most frequently referred-to topic group. This topic group includes all fan posts that make a reference to an individual product as opposed to the brand. Within this group, the most common subtopic was found to be *Product Suggestion* with 149 (47%) occurrences, e.g.:

> *"Hey Liebes Ok.- Team Wie Wärs Mit Nem Ok.- Energie Drink Apfel?? Wäre sicher so gut wie Exotic" (Original)*

> *"Hey Dear Ok.- Team How would it be with a new Ok.- Apple Flavored Energy Drink?? It would be for sure as good as the Exotic" (English translation)*

Within this category, fans were giving suggestions for new products or product variations, such as in the above given example where the new flavor was suggested, that the company should consider including in the product palette.

Product Affect, with 99 occurrences (31%), was found to be the second most commonly used sub-topic within the *Product* topic group. Posts belonging to this sub-topic expressed sentiment towards particular products, e.g.:

> *"ok,- ist das beste ;-) da ich in die schule gehe trinken alle am morgen , nachmitags, und abends ok. i love ok energy drinks ;-) <3"(Original)*

> *"ok,- is the best ;-) in my school everybody drinks ok in the morning, afternoon and evenings. i love ok energy drinks ;-) <3"(English translation)*

From the marketing perspective understanding both of these sub-topics is important: the first one for sensing the needs of the customers and providing possibility for product development, and the second one as an indicator of product acceptance.

From the remaining subtopics, *Technical details* regarding specific product *Feature* were present in 18 posts (6%), while the *Price* was mentioned in only 9 posts (3%), usually in the context of comparison with the competitor brands. Finally, a small proportion of posts contained *Complaints* (16 occurrences, 5%).

4.3.1.2. Sales

Within posts belonging to the *Sales* topic group, fans mostly referred to the issues of product *Availability* (47, 59%) and *Retail Channels* (26, 34%). Within the *Availability* sub-topic fans mostly expressed interest in the product delivery date for a particular sales location, or the launch date for a newly announced product, e.g.:

> *"wann kommt das neue energy in den kiosk?" (Original)*

> *"when comes the new ok.- energy drink??" (English translation)*

The *Stores* subtopic relates to opening specialized brand stores and new stores or store locations, both within Switzerland and abroad, e.g.:

> *"Gibt es bald einen/mehrere ok.- Laden?"(Original)*

> *"Will there soon be one/more ok.- stores?" (English translation)*

From the company's perspective, these topics can be used for evaluation of the interest in the brand. In addition, they can be used to map the sales volume or the demand for specific products to a particular geographical location.

4.3.1.3. Brand

Affect was found to be the most common subtopic (43, 94%) within the *Brand* topic group, e.g.:

"i <3 ok.-" (Original)

Since this is where users express their emotions toward the brand, from the marketing perspective it can be perceived as a measure for the brand attitude and strength.

4.3.1.4. Competitor

References to *Competitors* occurred in 4% of the posts in total (26 occurrences). This topic was partially used to express positive/negative *Affect* towards the competitor, but also to compare the *Features*, *Price* or *Product Range* to those offered by different brands, e.g.:

*"*Red Bull ist nicht ok.-" (Original)*

*"*Red Bull is not ok.-" (English translation)*

Assuming that the brand owners already know their competitors, this topic is of importance to the company since it allows identification of the perceived similarities and differences to the competitors. It also indicates the specific aspects of the products that users compare and expect to get from the brand, such as price or taste.

4.3.1.5. Facebook Contest

Facebook Contest refers to the responses by users to the entertainment actions undertaken by the moderators of the Facebook brand page, such as asking for-, or expressing gratitude for the outcome or prize, e.g.:

"...gibt es bald wieder einen ok.- Foto-Wettbewerb? ;-)" (Original)

"…will there soon be another ok.- photo contest? ;-)" (English translation)

The goal of organizing contests on Facebook brand pages is to increase the level of engagement of the fans. As such, it is recommended as a good practice by social media marketing practitioners[40]. However, this topic is not of specific interest from the marketing perspective since it does not reveal the perception of the brand or any potential problems.

4.3.1.6. Company

Company is an umbrella topic for the posts related to customer service. It includes *Praise* for the company itself, as well as for the Facebook strategy and moderation style, e.g.:

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[40] Using Facebook Contests to Boost Fan Engagement. http://addventures.com/blog/using-facebook-contests-boost-fan-engagement. Accessed 2012-07-12

> *"ich finde es geil das ihr im facebook seit & auch immer zurück schreibt bei fragen oder bitten :) das nenn ich interesse von kunden :)_x000D_ so jetzt trink ich zuerst mal ein ok energy ;)" (Original)*

> *"I think it's cool that you always write back to questions of requests :) I call that interest for customers :) _x000D_ so now I will drink on ok energy for the first time ;)" (English translation)*

Although rare, it is an indication of the "job well done" for the page moderator and the company in overall.

4.3.1.7. Environment

Environmental issues were addressed by the fans in only 3 posts, e.g.:

> *"Wiso setzt eine aufstrebende Marke wie Ok.- nich gleich von Anfangan auf umwelt verträgliches Matterial??? (Verpakungen, oder Nastücher die nicht aus dem Regendwald stammen) Hatt das mit Gelt oder mangelnder Inteligenz zutuhen??? Weittere gründe kann ich mir nicht vorstellen ausser vieleicht noch gnadenlose Ignoranz... wie immer Liebe Grüsse von eurem Krittiker"(Original)*

> *"Why doesn't one emerging brand like ok.- focus on environment friendly material right from the beginning??? Does it have something to do with the money or with the lack of intelligence??? Other reasons I can't imagine except maybe yet merciless ignorance… as always best regards from your critics" (English translation)*

Although rare and not directly related to marketing objectives, due to the high level of expressed criticism these posts should not be ignored. Instead, the company should react upon these posts to avoid an escalation which could potentially lead to fan loss, as in the case of the Swiss company Mammut[41].

It should be noted that not all of the fan posts were classified as belonging to a topic. Some of them (122, 20%) were written in a form of a "word play" or slogan, thus belonging to no particular topic, e.g.:

> *"ok...in the end" (Original)*

The action-object approach provided additional possibility for presentation and interpretation of the same results, centered on actions undertaken by the fans as an indication for the intentions for participation.

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41 Umweltaktivist gegen Mammut: Angriff am Gipfel. http://bernetblog.ch/2011/11/29/umweltaktivist-gegen-mammut-angriff-am-gipfel/. Accessed 2012-07-17

4.3.2. Intentions for Participation

When focusing on the "action" element of the applied method, eight post categories, which served as indication for the participation intentions, were identified: (1) *Suggestions & Requests* (170, 27%), (2) *Affect Expression* (169, 27%), (3) *Sharing* (165, 27%), (4) *Information Inquiry* (98, 16%), (5) *Complaints & Criticism* (23, 4%), (6) *Gratitude* (22, 4%), (7) *Competitor Comparison* (22, 4%) and (8) *Praise* (5, 1%). Distribution of the posts over categories is visualised on Figure 12.

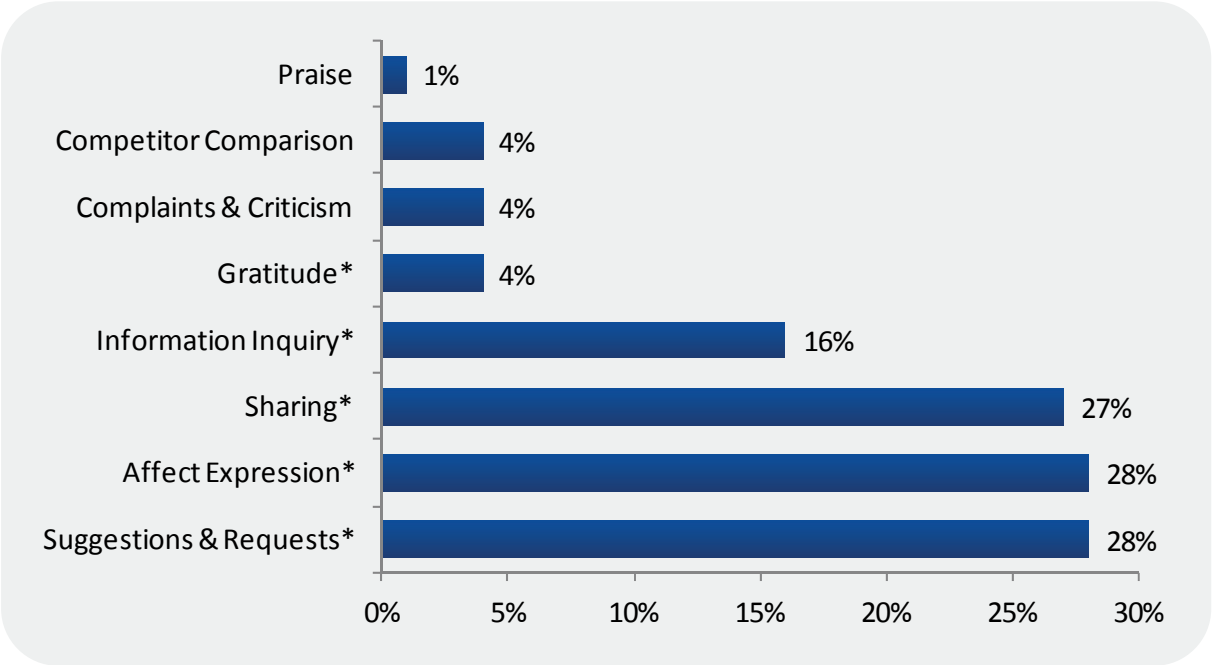

Figure 12: Intentions for participation on a Facebook brand page (*p < 0.0001)

The most common intentions for posting were found to be *Suggestions & Requests*, *Affect Expression* and *Sharing*, showing no significant differences in proportions among themselves. When compared to the *Information Inquiry*, *Sharing* occurred in a significantly larger number ($Z = 4.592$, $p < 0.0001$). Thus, *Sharing* also occurred in a significantly larger number compared to all of the remaining categories with smaller number of occurrence, i.e. *Gratitude*, *Complaints & Criticism*, *Competitor Comparison* and *Praise*. Since *Suggestions & Requests* and *Affect Expression* have a slightly larger number of occurrences compared to *Sharing*, the same reasoning applies. Furthermore, the proportion of *Information Inquiry* (16%) is significantly larger ($Z = 7.09$, $p < 0.0001$) compared to *Complaints & Criticism* (4%), thus also compared to the remaining categories with smaller number of occurrences. Finally, the proportion of *Gratitude* (4%) is significantly larger ($Z = 3.111$, $p < 0.0001$) compared to the proportion of *Praise*.

Each of the identified categories is explained and discussed in the following text.

4.3.2.1. Suggestions and Requests

Within *Suggestions and Requests* category, two related topic groups that occurred are *Sales* and *Product*. Fans tend to give suggestions for products, new ones, as well as improvements of specific features of existing products, e.g.:

> *"bitte ein ok.- energy drink ananas" (Original)*
>
> *"please a pineapple ok.- energy drink" (English translation)*

From marketing perspective this category is very valuable. It provides the possibility for idea gathering and product development, thus turning a brand page into a form of crowdsourcing platform.

4.3.2.2. Affect Expression

Affect Expression category refers to the fan posts that express sentiment towards a particular product or the brand. Posts belonging to this category occurred both with positive and negative connotation, targeted towards the brand, a product or a specific product feature, e.g.:

> *"also de mango findi mol ger ni fein, aber das isch au wieder gschmackssach"(Original)*
>
> *"I don't like the ok.- mango, but that is the matter of taste"(English translation)*

Affect was also expressed for competitors, often in a relation to the specific feature, such as the amount of carbonation in the drinks. Posts belonging to this category are of particular interest from a marketing perspective. They give clear indication on how the brand is perceived by the fans, what the popular products are and which specific features are the ones that are favoured by the customers.

4.3.2.3. Sharing

Sharing refers to a specific action undertaken by the fans by creating content with a goal of social engaging with other members of the brand page community. This study indicates that within a sponsored Facebook brand page fans share (1) current activities, (2) advices, (3) opinions, (4) action intentions, (5) needs, (6) information, (7) their feelings, (8) reflection on specific events and (9) rhetorical questions. A very common form of expression was a word play and/or a slogan which occurred in 92 posts (15%), e.g.:

"One ok.- a day, keeps the dok.-ter away"(Original)

4.3.2.4. Information Inquiry

Information Inquiry is an important category from the organizational aspect of the Facebook brand page. It identifies possible domains of interest of the page fans, e.g.:

"Wer hat eigentlich ok.- erfunden.?"(Original)

"Who actually invented the ok.- brand?" (English translation)

Since running a successful Facebook page requires full dedication, round-a-clock and prompt interaction with the fans, these insights reveal a need for different sources of information or a structure of the support team for the page moderator. Topics referred in this category include (1) *Brand*, (2) *Product*, (3) *Sales*, (4) *Company* and (5) *Contests*. Thus experts on these topics should be included in the support team.

4.3.2.5. Gratitude

Gratitude was mostly shown in case of winning a prize in one of the *Contests* organized within the Facebook page. However, those of interest from the marketing perspective expressed gratitude toward product launch (thus belonging to the *Sales* topic group) providing an initial insight into the acceptance of the new product, e.g.:

"Ich bin froh, dass es den ok.- energy drink jetzt auch in der light Version gibt! Danke ok.- :-)"(Original)

"I am happy that there is now an energy drink in the light version! Thank you ok.- :-)" (English translation)

As such, this category can be used to estimate sales of a new product.

4.3.2.6. Complaints and Critics

Complaints and Critics are painful, yet valuable part of SMM communication. As users feel free to express themselves in this medium, they offer the possibilities for improvement that would result in greater customer satisfaction. The most complaints occurred after the launch of a mobile phone product line which had several technical problems at the beginning, thus referring to a particular *Product*, e.g.:

"Ich habe heute ein ZTE San Francisco eingekauft: dead on arrival. Der touchscreen empfindet nichts. Die Hotlinenummer funktioniert auch nicht..." (Original)

> *"Today I bought a ZTE San Francisco: dead on arrival. The touch screen feels nothing. The hotline number also does not work…" (English translation)*

Within the same *Product* topic group, there were also a few *Price* complaints, usually in relation to the price offered by the competitor. Product availability, i.e. *Sales* was the second most referred topic in form of asking for a product delivery to a given location.

4.3.2.7. Praise

Within the analyzed dataset, *Praise* was targeted towards the discussed subtopics within the *Company* topic group:

> *„Ok.- Herzlichen dank für die Reklamtion weiterleitung... Hatt alles Geklappt, werde mich bei dem Kundendienst noch melden. IHR SEID SUPER!"(Original)*

> *"Ok.- Thank you very much for forwarding my reclamation... Everything worked out, I will yet get in touch with the customer service. YOU ARE SUPER!"(English translation)*

4.3.3. Topic-Category Matrix

The action-object approach used for this study clearly indicates that topics referred to within the posts (i.e. objects) and categories, as indication for intention for participation, (i.e. actions) are interconnected. Thus a matrix representation, as presented with Table II is suitable to identify the action-object pairs that appear within the observed dataset and to reveal the most common topic-category combinations.

Table II: Topic-category combinations and co-occurrence frequencies

	Product	*Sales*	*Brand*	*Competitor*	*Contests*	*Company*	*Environment*	*General*
Requests & Suggestions	**24% (149)**	3% (20)					0% (1)	
Expressing Affect	**20% (122)**		7% (43)	0% (4)				
Sharing								**27% (165)**

	Product	*Sales*	*Brand*	*Competitor*	*Contests*	*Company*	*Environment*	*General*
Information Inquiry	5% (29)	8% (49)	0% (3)		2% (10)	0% (3)		0% (4)
Complaints & Criticism	3% (16)	0% (4)				0% (1)	0% (2)	
Expressing Gratitude	0% (2)	1% (6)			2% (10)	0% (2)		0% (2)
Praise						1% (5)		
Comparison				4% (22)				

Apart from *Sharing* (27%), *Product - Requests & Suggestion* (24%) and *Expressing Affect* towards the *Products* (20%) were found to be the most dominant topic-category combinations. These numbers confirm that Facebook supports the identified goals of SMM, as presented in the related work section.

4.3.4. Sentiment Analysis

Understanding how people feel about the brand or specific product is one of the key elements for evaluation of social media initiatives (Hoffman and Fodor 2010, pp. 41-49). Brand sentiment expressed within the UGC can be differentiated as being positive, negative or neutral. Continuous monitoring of expressed brand sentiment is considered as good practice, mostly due to the fear of negative publicity as one of the most significant factors for considering social media as a marketing platform.

Facebook brand page offers the required platform to gather information on expressed sentiment and undertake an appropriate respond if needed. Thus, 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 manual categorization of the sentiment shared within the posts from the *Affect Expression* category.

Table III shows the frequency of occurrence for positive, negative and neutral sentiment towards brand or specific product. The results show that positive sentiment is shared far more often (25% of total posts) compared to the negative sentiment (2%).

Table III: Sentiment contained within the *Affect Expression* category

Sentiment	Occurrences (all)	Percentage (all)	Percentage (sentiment only)
Positive	150	25%	93%
Negative	11	2%	7%
Neutral	450	73%	
TOTAL:	**611**	**100%**	**161 (27%)**

The results presented in Table III could be biased by Facebook as underlying platform. Since the main idea behind joining a brand community on Facebook is *liking* the brand, it can be assumed that majority of fans have a positive attitude towards the brand, which is also reflected through the positive sentiment shared in the UGC.

Apart from the sentiment distribution, an additional analysis was performed in order to understand how fans express their emotions. Manual investigation of the posts containing sentiment revealed that emotions are displayed either via adjectives or through the usage of the following elements of internet slang: (1) emoticons, (2) interjections and (3) intentional misspelling.

Emoticons were used in 226 (37%) of the posts; 22% of those contained more than one emoticon (see Appendix IX for details).

An interesting form of emotion display was the usage of the "*<emotion>*" notion (6 occurrences), e.g.

> *"Ich hab Lust auf `nen Ok.- Cookie und ein Energy...Aber kein kiosk in der Nähe...*sniff*"(Original)*
>
> *"I want the new Ok.- Cookie and an Energy…But no kiosk near...*sniff*" (English translation)*

Further, interjections (29; 5%) that have occurred within the analyzed dataset and the enclosed emotions are listed in Appendix X.

Finally, intentional misspelling and punctuations marks are interesting from the perspective of sentiment analysis as an indication of emotion intensity. The recognized patterns included (1) capital letters, (2) repeating vocals and (3) punctuation marks, e.g.:

> *"Ig finde ds normale schwarze ok.- am beste. Das isch sooooo fein!!!!" (Original)*
>
> *"I find the normal black ok.- as the best. It is sooooo fine!!!!"(English translation)*

The usage of misspelling and punctuations was not as common as the usage of emoticons. Repeating vocals were present in only 19 posts (3%), capital letters in 27 (4%), while punctuation marks in 105 posts (19%). Still they are to be taken in account for the automatic sentiment analysis which could simplify the sentiment monitoring by avoiding the time consuming manual coding even in cases where the language represents a barrier for automatic opinion mining.

4.4. Discussion and Implications

4.4.1. Implications for Social Media Marketing

In order to successfully run a Facebook brand page as a part of the SMM approach, companies need to understand their users by learning how and why they interact on the brand pages. Within the study presented in this chapter, this problem was addressed from two perspectives: (1) understanding the topics referred to within the UGC and (2) understanding the intentions for participation on Facebook brand pages. In addition, a final overview of the valence and modes for sentiment expression was provided to address the fear of negative publicity.

The results presented in the previous section confirmed that posts shared on Facebook brand pages represent a valuable source of knowledge for companies. To summarize the previously presented findings regarding the topics analysis, the following implication can be formulated:

> *I1: Companies utilizing Facebook for marketing purposes should perform continuous topic analysis since UGC reveals: (1) perception of the brand, (2) acceptance of a new product, (3) most favoured products and features, (4) required products and features, and (5) locations with great volume of sales. In addition, by listening to the page conversation*

companies could identify (6) existing problems and (7) perceived competitors.

In addition, with 27% of the posts belonging to the *Requests & Suggestions* category, Facebook brand pages provide the possibility for generation of ideas about new products and services. Thus:

I2: Companies utilizing Facebook for marketing purposes should perform continuous topic analysis since UGC can be used for product development.

Organizationally, the topics of conversation can be used to understand what different sources of information should be available to moderators to provide timely answer to the fans on Facebook brand pages, i.e. members of the support board behind the moderator that can be addressed when a specific question is posed. Looking at the main topic groups as well as those referred within the Information Inquiry category, this study indicates the following:

I3: To successfully run a Facebook brand page, the moderator needs a support board consisted of following experts: (1) sales, (2) logistics, (3) company/brand information (producer, founder, history, etc.), (4) product information, and (5) environmental issues.

Further, this study confirms that Facebook is a suitable platform for SMM which supports the SMM goals for (1) building brand awareness, (2) gathering insights and knowledge for future steps, and (3) community engagement in dialog. This arguing is based on the results showing that *Product*, *Sales* and *Brand* are the three most discussed topics, while *Requests & Suggestions*, *Expressing Affect* and *Sharing* are the most common intentions for participation.

Furthermore, the topics and categories, i.e. intentions for participation in brand communities on Facebook, were shown to be interconnected. Therefore, the following managerial implication can be drawn:

I4: The topic-category matrix can be used by practitioners as a tool that enables measurement of success of SMM utilization over time.

The results presented in the previous section showed that on the ok.- brand page *Product - Requests & Suggestion* (24%) and *Expressing Affect* towards the *Products* (20%) were the most common combinations which are in line with the company's SMM goals.

Finally, the results of the sentiment analysis showed that positive sentiment is expressed far more often compared to negative. Still, based on existing examples, a recommendation can be given that:

> *I5: Negative publicity and fan loss can be avoided by continuous monitoring and appropriate and timely response to negative content containing criticism and complaints.*

4.4.2. Implications for Opinion Mining

Apart from the managerial implications, this study provides the possibility to address the challenges of automatic opinion mining by understanding the format of the UGC on Facebook brand pages. The obtained results show that automatic opinion mining can be achieved by creation of the standardized lexicon for the Internet slang, including: (1) slang abbreviations, (2) emoticons and (3) interjections. Further, the number of emoticons, repeating vocals and punctuation marks can be used as a measure for the sentiment intensity.

For the specific domain of Swiss German language there are still many open questions such as: (1) to which extent can German lexicon be applied for automatic analysis and (2) how and if it is possible to overcome the challenge of not having rules for the written form. The tagged dataset from this study could further be used as training set for machine learning algorithms for automatic opinion mining of the content shared on brand pages from the Swiss German speaking region.

4.5. Summary, Limitations and Future Work

This study presents an analysis of the UGC on a Facebook brand page. The obtained results identified seven major topic groups: (1) *Product*, (2) *Sales*, (3) *Brand*, (4) *Competitor*, (5) *Facebook Contest*, (6) *Company* and (7) *Environment*. In addition, eight intentions for participation were revealed: (1) *Suggestions & Requests*, (2) *Affect Expression*, (3) *Sharing*, (4) *Information Inquiry*, (5) *Complaints & Criticism*, (6) *Gratitude*, (7) *Competitor Comparison* and (8) *Praise*. Finally, their interconnection was presented through the topic-category matrix. Based on the obtained results, implications were drawn primarily for SMM, but also for automatic opinion mining.

The main limitation of this study is a relatively small dataset extracted from only one Facebook page. In turn, the longitudinal approach offered more insights by observing greater variety of addressed topics, since certain

subtopics occurred only within a limited number of posts (e.g. *Environment*) and during a limited period of time (e.g. the subtopic *Technical Details* occurs for the first time on December 4th, 2010). Furthermore, this study provides a detailed analysis for the specific domain of a Facebook brand page, managed by the company offering FMCG.

The analysis presented in this paper can be used by marketing practitioners as a measure for successful SMM utilization over time. Automation of the proposed methods would provide the possibility for real-time monitoring and timely reaction. This could be achieved by replacing the manual process of content analysis with a system capable of automatic topic classification and sentiment analysis. Further optimization of the existing opinion mining techniques, addressing in particular the specific language structure and multilingualism issues would contribute in this direction.

Finally, extending the performed analysis over additional brand pages and different categories of Facebook pages would provide the possibility for generalization of the obtained results.

Summary of Main Findings

- Facebook is a suitable platform for SMM which supports the SMM goals for (1) building brand awareness, (2) gathering insights and knowledge for future steps, and (3) community engagement in dialog.
- UGC on Facebook brand pages reveals (1) perception of the brand, (2) acceptance of a new product, (3) most (and least) favored products and features, (4) required products and features, and (5) locations with great volume of sales.
- By listening to the conversation on the Facebook brand page, companies could identify: (1) existing problems, and (2) perceived competitors.
- Facebook brand pages provide the possibility for generation of ideas about new products and services.
- On Facebook brand pages, positive sentiment is expressed far more often compared to the negative.
- To provide timely answer to the fans, as expected on social media platforms, the moderator needs a support board consisted of following experts: (1) sales, (2) logistics, (3) company/brand information and (4) product information.
- The topic-category matrix can be used as a tool for practitioners, which enables measurement of success of SMM utilization over time.

5. Monitoring Trends on Facebook

Automated text mining provides the opportunity to the companies to extract meaningful information from the UGC on their Facebook brand pages, by avoiding the time consuming, manual content analysis. As such, creation of a system capable for automatic topic extraction is a worthy goal. In addition, this approach enables companies to monitor the conversation outside their own brand pages, by:

- Analyzing the topics on related brand pages created for the company, brand or individual products by enthusiastic individuals, in order to be prepared for fast reaction in case of negative publicity;
- Monitoring of conversation on brand pages of competitor companies, in order to learn from their practices and potentially attract/convert their fans; and
- Monitoring of general trends on the underlying platform, since external events might also have an influence over the company's operation.

The study presented in this chapter addresses the research questions RQ4: "How to monitor trends over the UGC on social media?" and RQ5: "What are the characteristics of trending topics?" presented in Chapter 1.2.1.1: "User-Generated Content on Social Media Platforms". It proposes a system for automated topic identification and trend monitoring over Facebook posts. In addition, it reveals differences between the trend characteristics. Since providing information regarding external events is a practice commonly used by practitioners (see Chapter 7: "Customer Engagement on Facebook Brand Pages"), this approach offers the opportunity for gathering ideas on possible topics to be addressed within this content category. Moreover, understanding which topics that appear in traditional media are suitable for social media environment might increase the level of engagement over this content category. Finally, the analysis of the temporal distribution of trending topics

shows which topics are referred to by Facebook user at which time of the day and might be used for selection of appropriate posting time.

This study was originally published as: “Monitoring Trends on Facebook” (Pletikosa and Michahelles 2011a, pp. 895-902). Thus this section contains excerpts from this publication which will not be referenced further in the text.

5.1. 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. The value of the content generated on online platforms as a source of information was soon recognized, resulting in individuals turning to social media platforms as a source of real-time news and opinions (Kontostathis et al. 2003, pp. 185-224).

This form of usage of social media platforms has further been supported by the platform providers, by offering the possibility for searching through the vast amount of public status updates to monitor content or find temporally relevant information (Simm et al. 2010, pp. 552–557). In addition, they have offered the possibility to access the public status updates through their search APIs, resulting in a burst of commercial and research efforts to gather knowledge through analysis of the shared content.

Detection and analysis of trends offer valuable insights into the topics that attract the attention of a large fraction of SN users. Public opinions in form of trends are interesting not only for individuals, but also for:

- News reporters - pointing to the fast-evolving news stories (Cheong and Lee 2009, pp. 1-8; Kwak et al. 2010, pp. 591-600);
- Sociologists – revealing the “spirit of the times” (Naaman et al. 2011, pp. 902-918);
- Opinion tracking companies - for prediction of elections outcome (Tumasjan et al. 2010, pp. 178–185), stock market (Zhang et al. 2011, pp. 55-62), or movie revenue (Asur and Huberman 2010, pp. 492–499), and,
- Marketing professionals - for brand image monitoring, “buzz” listening and benchmarking against competitors (Goorha and Ungar 2010, pp. 57-64; Kasper and Kett 2011, pp. 662-669).

As the number of available sources and the amount of online information increase, individuals and companies interested in fast discovery of trends through monitoring of the conversation on social media platforms need to rely on the tools capable of automatic topic detection and monitoring. This has motivated research into text analysis and application of the existing information retrieval and trend detection techniques to social media in order to benefit from the knowledge enclosed within the UGC.

Trend monitoring over Twitter stream has already been the subject of attention of scholars and professionals, resulting in numerous modified and new algorithms for information retrieval and commercial online tools. However, when it comes to Facebook, there is no existing research focusing on the topic of trend detection. In addition, there is a single commercial implementation, i.e. Facebook Trends[42], limited to the discovery of the trending topics over the public posts from German speaking Facebook users, based on the term frequency. This situation is due to the fact that Twitter provides the possibility for real-time data collection, which is not supported by Facebook. In addition, privacy policies on Facebook introduce limitations into the amount of available data. Still, UGC on Facebook is a valuable source of insights, since Facebook is the largest social network with more than 1 billion pieces of content created on a daily basis[43].

This chapter provides twofold contribution towards trend monitoring over Facebook. First, a system for trend monitoring, based on the characteristics of the posts shared on Facebook, is introduced and evaluated. Then, based on the obtained results, a categorization of trending topics is proposed. Finally, in order to increase the understanding on emerging trends on Facebook, an analysis of the characteristics of the proposed trend categories is provided with a focus on the distribution and information diffusion.

The continuation of this chapter is structured as follows. Section 2 describes the used methodology, while Section 3 presents the results of the evaluation. Section 4 describes the characteristics of trends on Facebook. Finally, Section 5 provides a summary, discussion on the limitations of this study and proposes ideas for future work.

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42 Facebook Trends. http://www.facebook-trends.de/. Accessed 2012-07-10

43 Facebook Statistics. http://newsroom.fb.com/content/default.aspx?NewsAreaId=22. Accessed 2012-06-11

5.2. Method

Trend monitoring over Facebook public posts could be divided in two major steps: (1) data collection, and (2) trend detection. Providing (near) real-time trend monitoring over the full set of public posts shared on Facebook assumes data collection that is: (1) continuous, (2) real-time, and (3) provides access to the full scope of public posts. Trend detection is commonly based on (1) topic identification, and (2) term clustering.

The continuation of this section explains the details of both steps of the process and provides evaluation of the presented approach.

5.2.1. Data Collection

Data collection presents one of the challenges of trend detection over the UGC on Facebook. While Twitter allows high-throughput, real-time access to various subsets of public and protected Twitter data through the Streaming API[44], Facebook provides only limited functionality through its Graph API already introduced in Chapter 3.4.2: “Facebook Graph API”.

The Graph API does not provide the possibility to receive posts in the form of a real-time stream, thus the search feature was used instead, returning a list of public posts for a given keyword upon a query with the following format:

```
https://graph.facebook.com/search?q=<KEYWORD>&type=post&limit=<NL>
```

In order to collect all the public posts, a simple algorithm which performs a search taking each ASCII character as a keyword, thus providing a loop of 26 search queries, was applied. In addition, the Graph API offers the *limit* parameter (NL) for the search query which defines the number of returned post objects, with the default value of 25, and maximum of 500 posts. In our system we have used the maximum value to increase the performance in terms of processing time.

In case there are more than NL available posts for the given keyword, the obtained JSON response contains the URL for the next query. This results in the possibility of having more than one sub-query for a given keyword, depending on the selected time interval. The pseudo-code listing for data collection is provided in Algorithm 1.

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[44] The Streaming APIs. https://dev.twitter.com/docs/streaming-apis. Accessed 2012-07-10

Algorithm 1: Collection of public posts from Facebook

```
1  until = getLastCollectionTime();
2  for each asciiChar in asciiList do
3     nextURL = collectPosts (asciiChar, until);
4  until (nextURL != null)
```

It can be seen from the above listing that a variable named *until* is used in the code as a control variable. This variable represents the timestamp of last data collection. Thus, when the post is received and processed in the *collectPosts()* method, if the timestamp of its creation is prior to the timestamp of the last data collection, the loop ends, since this post was already stored in the database in the previous data collection cycle.

The selection of the interval duration for data collection i.e., the time between two data collection cycles, was based on the following two premises: (1) the data collection interval should be long enough to be able to capture trending topics, and at the same time, (2) it should be short enough to provide possibility for near-real time monitoring while overcoming the processing challenges over the large datasets. Based on this reasoning, and the results of the several iterations of parameter tuning of our system, an interval of 10 minutes was selected.

5.2.2. Dataset

Using the previously described algorithm, collection of the posts was performed from July 22, 2011 until July 26, 2011. This resulted in 2,273,665 public posts in total. The average number of posts fetched with the proposed algorithm on a daily basis was 568,416.

These particular dates were selected for the following reasons: (1) two big events that captured the attention of the people on other forms of media happened during these days, and (2) an assumption was made that people access social networks and interact more frequently on weekends. The two different events, both causing great emotional reaction of the public, which occurred during this period are:

- The terrorist attack in Norway[45], at 13:26 GMT on July 22nd, when 77 people died and 96 more were injured, and
- The death of the English singer and songwriter Amy Winehouse[46] who had been attracting attention with her great talent, but also a very controversial life style, at the age of 27, on July 23rd, at 14:54 GMT.

To understand the characteristics of the Facebook posts relevant for the trend detection we performed linguistic analysis over three sets of posts. The obtained results are presented in Table IV.

Table IV: Linguistic statistics for public posts on Facebook

	Average Length		
	5K posts	**50K posts**	**100K posts**
Sentences	1.43	1.44	1.43
Words	17.43	17.53	17.43
Characters	103.89	103.39	102.80
	Language		
English	78%	78%	77%

From Table IV, one could see that there are no significant differences between the three sets. The average number of sentences in a post is approximately 1.4. At the same time, the average number of words is approximately 18, a bit higher compared to the 16 words in a tweet (Goorha and Ungar 2010, pp. 57-64). However, looking at the full dataset, while the average post length in character didn't significantly differ from our results (108), the maximum length was found to be 754 characters, which on average corresponds to approximately 10 sentences and 122 words and is significantly higher than the 140 allowed characters per tweet.

In addition, tweets allow only for textual input, while Facebook supports different post media types: (1) *status*, (2) *video*, (3) *link*, (4) *photo* and (5)

45 Norway attacks. http://en.wikipedia.org/wiki/Norway_attacks. Accessed 2012-06-11

46 Amy Winehouse. http://en.wikipedia.org/wiki/Amy_Winehouse. Accessed 2012-06-11

music. Distribution of each of these types over the obtained dataset is presented on Figure 13.

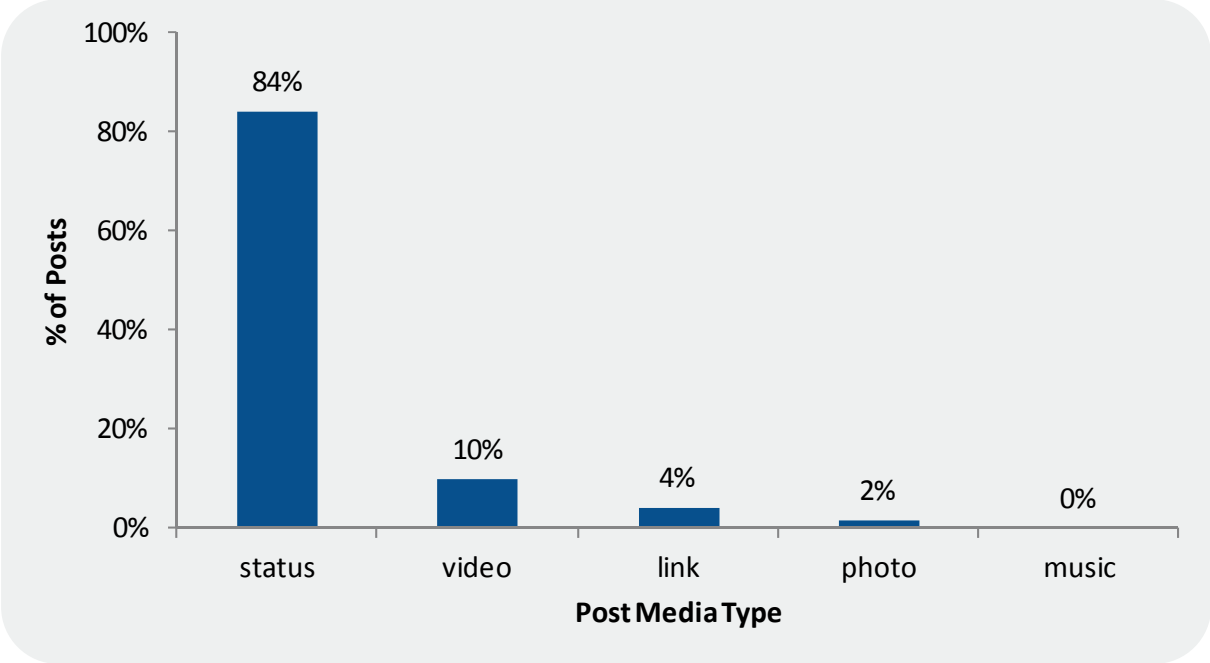

Figure 13: Distribution of public Facebook posts by post media type

It can be seen that 84% of the posts (2,129,353 occurrences) are written in form of the *status* media type, followed by *videos* (10%, 249,774), *links* (4%, 107,984) and *photos* (2%, 41,967). *Music* posts, as a sub-type of video media type, were present with only 350 occurrences (0%) in the obtained dataset.

In terms of the language used in the posts, based on the classification performed with the LingPipe API[47] over the three datasets, English was found to be the dominant language, present in 78% of the posts, as shown in Table IV.

Finally, an analysis of the cumulative distribution of posts over time of day was performed, assuming that it might also have an effect over the distribution of the trending topics. Obtained results are presented on Figure 14.

[47] LingPipe 4.1.0. http://alias-i.com/lingpipe. Accessed 2012-07-10

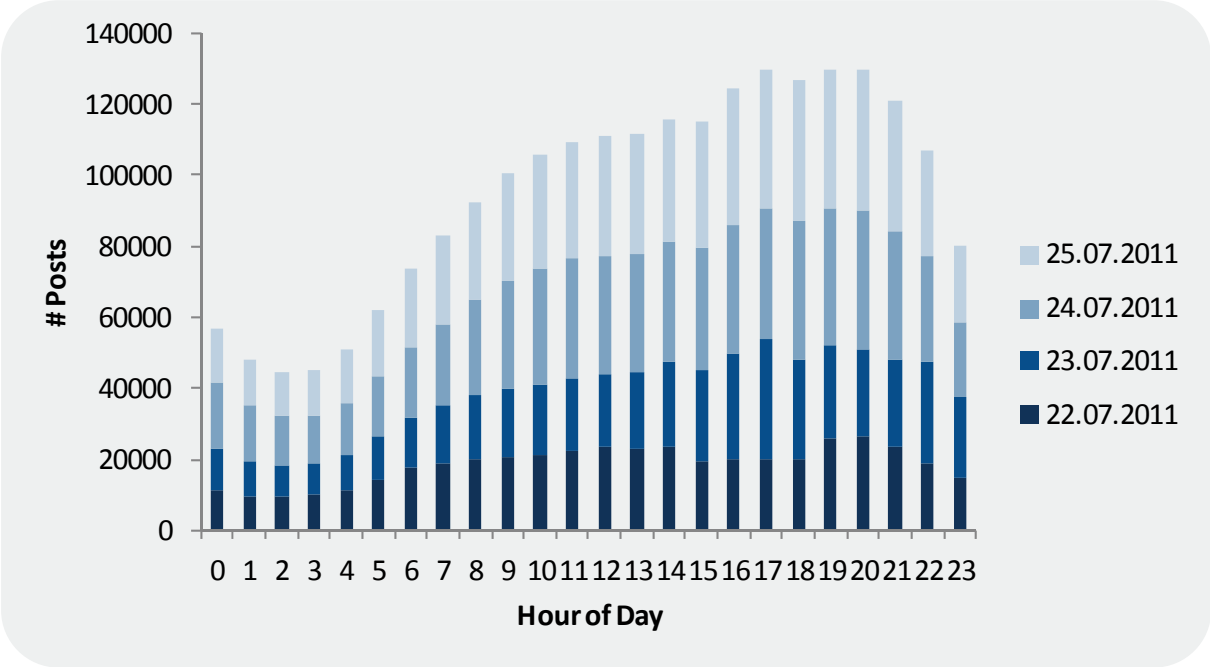

Figure 14: Distribution of public Facebook posts by hour of day

It can be seen that the lowest level of activity in terms of number of shared posts over the selected time interval occurred at 2:00am, while the highest number of posts were shared between 5:00pm and 9:00pm.

The presented results are used as a basis for the further reasoning.

5.2.3. Trend Detection

5.2.3.1. Post Topic Identification

Based on the results of the analysis of the post type distribution, trend detection was performed only over the content shared in form of *status* posts. Following the common approach (Jones 1972, pp. 11-21) the method begins by discovery of the most significant terms within the collection of Facebook public posts. In the context of this study, a *term* is an n-gram with a length from 2 up to 5 words belonging to the same sentence within the post. Usage of bigrams as a lower limit was based on the results of the experiments with different lengths where unigrams introduced too much noise by having common words appearing high on the weighted list while carrying no topic information (e.g. “love”).

Before the creation of the lists of n-grams, a preprocessing of the posts was performed by applying (1) stop-words filtering, based on the predefined list only for English, and (2) removing the URLs from the posts.

For the weighting of the terms, the "Term Frequency – Inverse Document Frequency" (TF-IDF) approach was used, due to its simplicity. The method assigns a weight to a term 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 which contain the given term. Therefore, the basic form of the formula would be:

$$w(t_i) = tf(t_i, d_j) * \log 2 \frac{N}{df(t_i)} \quad (1)$$

where *N* is the total number of documents in the corpus, *tf(ti, dj)* is the frequency of term *ti* within the document *dj*, and *df(ti)* is the number of documents in the corpus containing the term *ti* (Karlgren 2010, pp. 295-336). However, this formula was found to be unsuitable for the content shared on social networks, such as Facebook and Twitter, because of the limited length of the posts, which would reduce the value of the term frequency component in the equation. Furthermore, calculating the frequency over the full corpus would result in having a single document, thus losing the inverse document frequency component (Mathioudakis and Koudas 2010, pp. 1155-1158).

In order to overcome this problem, following the example of the previous work over Twitter (Mathioudakis and Koudas 2010, pp. 1155-1158), a concept of hybrid document was used. Hybrid document represents a collection of posts *P = {p1, p2, …, pK}*, obtained within a timeframe *T*, which corresponds to the previously introduced interval for near-real time data collection (see Chapter 5.2.1: "Data Collection" for details). Each time frame *T* represents a separate dataset described by a separate weighted list. In addition, based on the results of the linguistic analysis, an assumption is made that there might be more than one occurrence of the same term within a post. For that reason, in case of large datasets, such as the one explored in this study, and due to the smoothing shape of the logarithm function, a term that appears more than once in a single post might have higher weight compared to a term which occurs in several posts. To avoid this, when calculating the term frequency, instead of the sum of all occurrences of a term over all posts $p_j \in P$, only a single occurrence of a term per post is calculated. Based on this discussion, the modified version of the above formula proposed for content shared on Facebook is:

$$w(t_i) = tf(t_i) * \log 2 idf(t_i) \quad (2)$$

$$\mathrm{tf}(t_i) = \frac{\#\mathrm{PostsContainingTerm}}{\#\mathrm{AllTermsOverP}} \tag{3}$$

$$\mathrm{idf}(w_i) = \frac{|P|}{\#\mathrm{PostsContainingTerm}} \tag{4}$$

where *P* is the collection of all posts in the corpus, i.e. the hybrid document: *P = {p1, p2, …, pK}.*

5.2.3.2. Post Clustering

Post topic identification results in an ordered list of the most significant terms in the corpus, where terms refers to the n-grams whose length vary from 2 to 5 words. The next step towards trend identification is to cluster together those terms that belong to the same topic. For example, terms “Norway shooting” and “terrorist attack” should be grouped within the same topic group since these two terms refer to the same topic. In order to achieve this, a post clustering is performed. The process consists of two steps (1) clustering by distribution, and (2) clustering by co-occurrence. Details of each of these steps are provided in the continuation.

Clustering by Distribution

Clustering by distribution represents a combination of (1) the comparison of the term weight among different terms, and (2) the intersection of the related documents, i.e. Facebook public posts. The goal of this approach is to eliminate the multiple occurrences of the similar n-grams with different lengths originating from the same posts. For example, both terms, “amy wihehouse” and “amy winehouse dead”, extracted from the same post, will appear as separate terms in the list, having the same weight and containing the same information, which introduces redundancy. Once the grouping is done, each group is replaced with the n-gram with the maximal length since it contains maximum information regarding the topic. The algorithm listing of the proposed method is provided in the continuation:

Algorithm 2: Clustering by distribution

```
1  for each term in sortedWeightList do
2    if (termWeight != previousTermWeight) then
3      createNewGroup(term);
4    else
5      for each group in topicGroups do
6        if (getPosts(group) = getPosts(term)) then
7          addTermToGroup(term, group)
```

Algorithm 2: Clustering by distribution

```
8            else
9               createNewGroup(term);
10           end
11        end
12     end
13     weight = termWeight
14  end
```

It can be seen that for each term in the list, the term weight is compared to the weight of the previous term in the list to determine if they are equal. If this is not the case, then a new group for the term is created. Otherwise, if all posts from the group are the same as those that the term belongs to, then the term is added to that group. If this is not the case, it means that despite the same weight, the terms do not originate from the same posts, and as such they should not be placed in the same group in this step.

Clustering by Co-occurrence

Once the redundancy is removed, the next step is to group related terms together. This is done through the clustering by co-occurrence approach, which is based on the assumption that terms that appear frequently in same posts belong to the same topic. This step is used to group those terms that are not semantically similar and belong to different posts, but still refer to the same topic, such as “amy winehouse” and “drug addict”. The proposed algorithm is presented in the following listing:

Algorithm 3: Clustering by co-occurrence

```
1  for each term in sortedWeightList do
2     for each group in topicGroups do
3        if (getPosts(group) ∩ getPosts(term) != 0) then
4           addTermToGroup(term, group)
5        else
6           createNewGroup(term);
7        end
8     end
9  end
```

It can be seen that this algorithm is again based on the intersection of the post sets related to a particular term. The algorithm starts from the first term in the

list (sorted according to the weight) and tries to find a group for which the intersection of the posts is not an empty set. Once the first group that satisfies this condition is found, the term is added and the processing continues to the next term.

The resulting list of topic groups, represented each as a set of terms and a set of corresponding posts for each of the included terms, is ordered in accordance to the highest term weight in the group.

5.3. Evaluation

In order to perform a preliminary evaluation of the proposed algorithm the common approach of measuring the precision and recall was applied (Raghavan et al. 1989, pp. 205-229). For that purpose a review of the results obtained from 10 experiments, each collecting and processing 1000 posts from different time intervals, was conducted. For each experiment, evaluation was performed over the same three topic groups that commonly occurred over the observed time interval. For each topic group, a list of corresponding posts was examined. In addition, in case of the Norway incident, two evaluations were conducted: one assuming that the group containing the majority of the related posts is the representative for the "true positive" categorization (denoted as "max posts" in the continuation), and the second one based on the selection of the topic group that most accurately describes the actual event as a representative for the "true positive" score (further denoted as "best fit"). The results of the evaluation are presented in Table V.

Table V: Results of the preliminary evaluation of the trend extraction algorithm

Topics	Measures		
	Precision	**Recall**	**F-measure**
Amy Winehouse	0.9475	0.7748	0.8510
Norway (max posts)	0.0736	0.6124	0.1303
Norway (best fit)	1.0000	0.0621	0.1164
Harry Potter	0.8344	0.8589	0.8115
Average Values	0.7139	0.5771	0.4773

The obtained values for precision and recall showed that the proposed approach generates relatively good results for two of the analyzed topics:

"Amy Winehouse" and "Harry Potter". The commonality between these two topics lies in the fact that they are both described with a personal name containing two words, which corresponds to the minimum n-gram length used in the method.

In case of the Norway incident, the clustering algorithm didn't perform as well as for the other two topics. Instead of having a single topic group related to the events in Norway, the algorithm placed a majority of the posts within the "Amy Winehouse" group as a result of the co-occurrence clustering, while the remaining of the related posts were scattered over multiple topic groups, mostly consisted of a single post. This resulted in a very low value of the F-measures for both approaches. The main difference between Norway and the previous two topics is that it has occurred in a very small number of posts and with a great diversity in terms of used words within the posts resulting in clustering problems.

The average values presented in the Table V indicate that, on overall level, the proposed algorithm performs relatively well. Still, further improvement through usage of more advanced text mining methods is needed to overcome the previously described difficulties.

5.4. Trend Characteristics

5.4.1. Trend Categorization

Applying the previously described algorithms revealed that there are differences between the topics that appear as trends. In order to analyze and understand these differences the following three categories of trending topics are proposed:

- *Disruptive events* are trending topics which correspond to the events that occur at a particular point in time and cause reaction of Facebook users on a global level, such as the earthquake in Japan, Wimbledon finals, etc.

- *Popular topics* might be related to some past event, celebrities or products/brands that remain popular over a longer period of time, such as Coca Cola, Michael Jackson, etc.

- Finally, *daily routines* correspond to some common phrases such as "good night", "birthday wishes", etc.

For the further analysis, topic representatives for each of the previously described categories were selected:

- The death of “Amy Winehouse” and the “Norway attacks”, as examples of *disruptive events*,
- “Harry Potter”, as a representative for the *popular topic* contained within the obtained dataset, and
- “Happy Birthday” as a common practice and a typical *daily routine* on Facebook

In the continuation, differences between these categories in terms of a distribution through the shape and volume of the shared information are presented. In addition, an analysis of the speed and scale of information distribution on Facebook was performed, to explore the possibility to use Facebook as a news media.

5.4.2. Distribution of Trending Topics over Time

The distribution in terms of the volume of the posts shared on Facebook regarding a certain topic is a clear indicator of a level of interest of users for the related topic. In addition, the shape of the distribution is an indicator of a topic belonging to the category of *daily routines* that is always present in the conversation at some relatively equalized level, or if it relates to an event occurring at a particular point in time.

Understanding the differences between distributions that relate to the *daily routines* and *popular topics* on one side, and the distributions related to *disruptive events* on the other, gives the possibility to train the systems for automatic trend detection in order to distinguish between these different types of trends. Figure 15 to Figure 18 illustrate the time series for the previously selected topics from each category in the observed time interval.

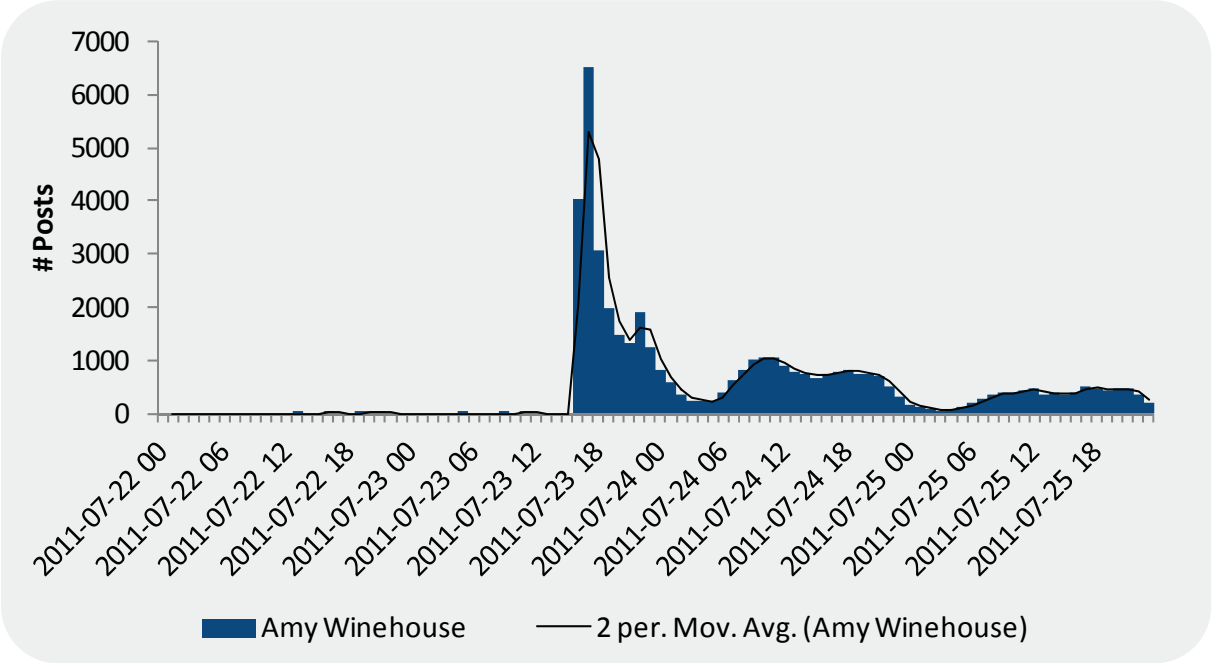

Figure 15: Time series of posts related to a disruptive event: "Amy Winehouse"

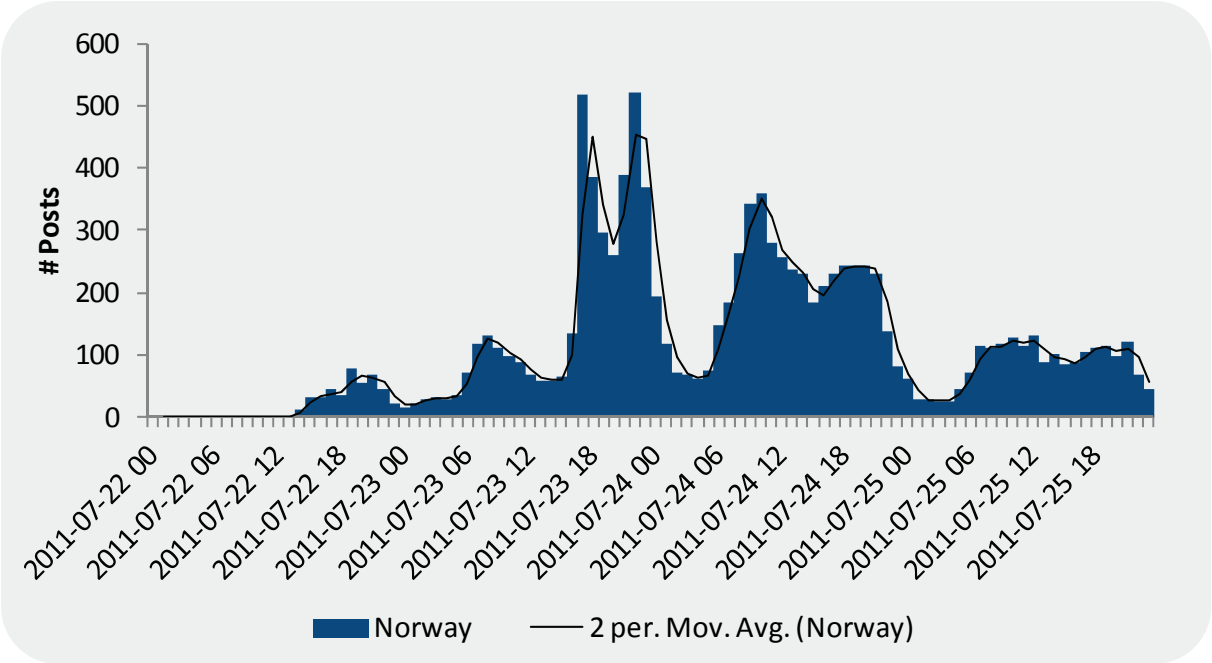

Figure 16: Time series of posts related to a disruptive event: "Norway"

It can be seen from Figure 15 that the topic of "Amy Winehouse" has a burst of posts immediately after the time of her death. The same effect, although not with such intensity, can also be seen for the "Norway attack" as visible from Figure 16. An interesting observation is that at the day of the event, the number of posts related to Norway is significantly lower compared to the next day. Furthermore, the big peak on the Norway graph corresponds with the initial peak for "Amy Winehouse". Analyzing the post clusters obtained

through our algorithm showed that these two topics indeed appeared in same posts, e.g.:

> *"Supposedly Amy Winehouse is dead. Though I think Norway deserves more sympathy. " (Original)*

Regarding the "Harry Potter" topic, illustrated on Figure 17, and "Happy Birthday" topic, illustrated on Figure 18, the curves show almost regular peaks throughout the interval as could be expected. However, these variations in the volume are not as big as those in the case of *disruptive events*.

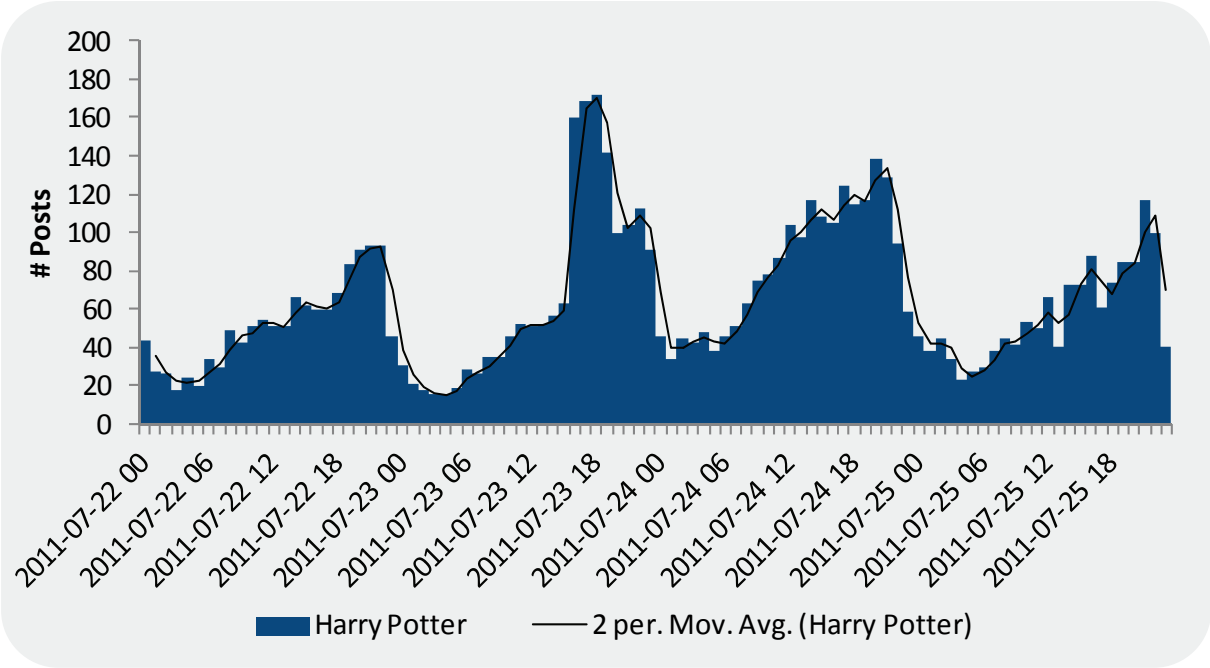

Figure 17: Time series of posts related to a popular topic: "Harry Potter"

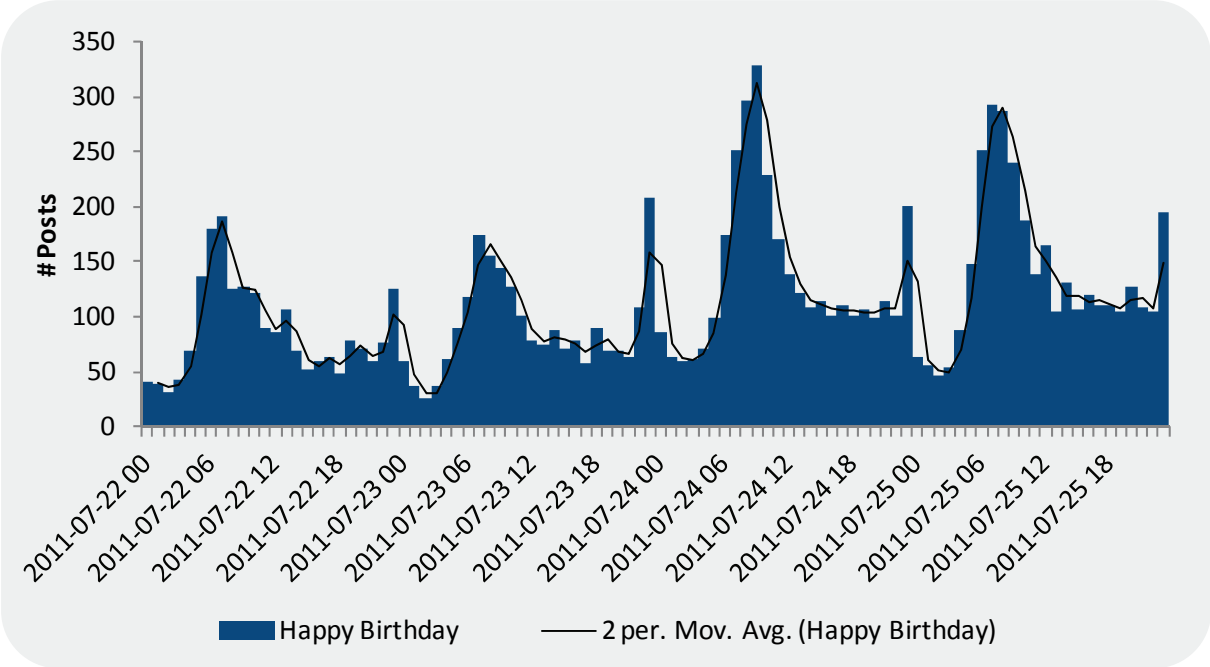

Figure 18: Time series of posts related to a daily routine: "Happy Birthday"

Comparison to the cumulative distribution of posts over time of day shows that the peaks on the *popular topics* correspond with the peaks on the daily post distribution graph, while peaks for *daily routine* are the opposite. This result can be explained assuming that Facebook users want to congratulate their friends as early as possible. On a more general level, *daily routines* are usually related to a certain period of time in a day, for example, "good night" appears as a trending topic only in the evenings. Furthermore, these two topics are present and trending during the whole time interval, indicating a commonly occurring topic in conversations on Facebook, but not something new. Descriptive statistics for the selected topics are presented in Table VI.

Table VI: Descriptive statistics for selected topics from different trend categories

Measures	Trending Topics			
	Amy Winehouse	**Norway**	**Harry Potter**	**Happy Birthday**
Mean	464.66	114.78	64.44	113.66
Standard Deviation	888.69	115.31	36.27	63.86
Kurtosis	25.02	2.16	0.46	1.70
Skewness	4.44	1.50	0.96	1.35
Min/Max	0 / 6516	0 / 520	15 / 172	25 / 328
Sum	44607	11019	6186	10911

The obtained values indicate big differences in the distributions. Differences in standard deviation can be used as an indication of *disruptive events*, while sum and mean do not provide such a clear distinction. In addition, kurtosis corresponds to the variations between peaks and has higher value for the *disruptive events* compared to the popular and common topics. Finally, skewness illustrates that the majority of the posts have been grouped at one segment of the time interval, again as an indication of a significant peak in the distribution.

5.4.3. Speed and Flow of Information Diffusion

Time of occurrence of the first post regarding a certain topic is interesting from the perspective of evaluating the possibility to use Facebook as a news media. In addition, the speed of the information diffusion can be measured by the time interval between the event and the time the topic became a trending topic. Figure 19 and Figure 20 illustrate the distribution of posts for both big events during the first two hours.

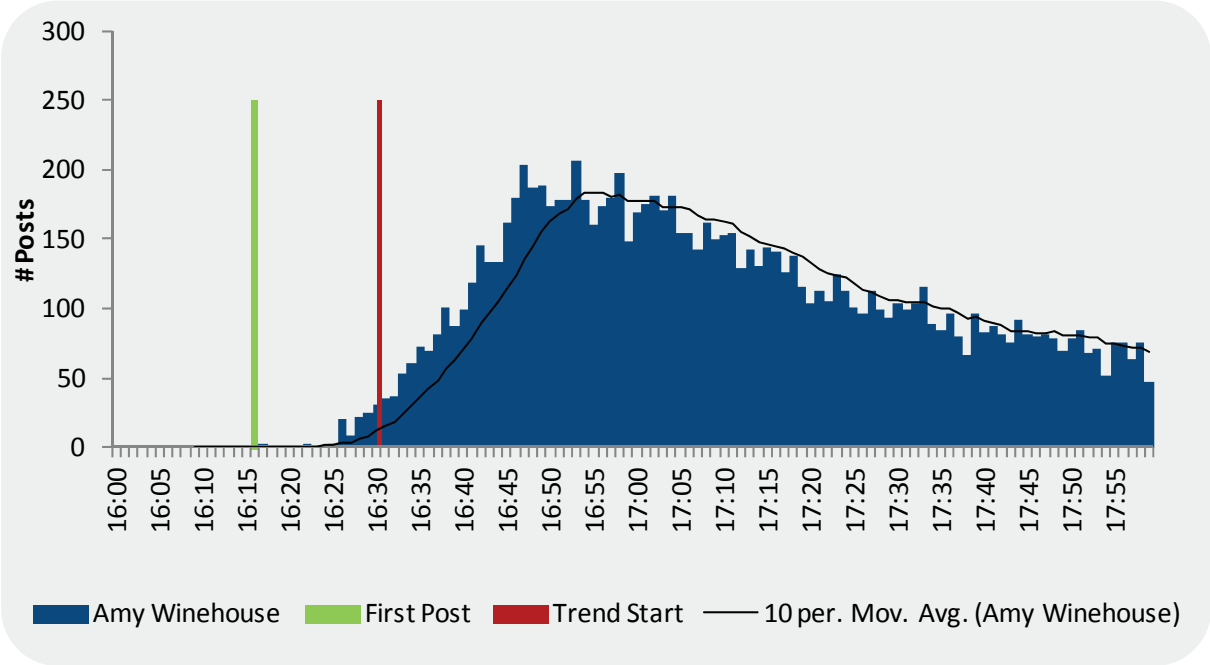

Figure 19: Information diffusion for disruptive event "Amy Winehouse"

It can be seen that the first post for Amy Winehouse occurred at 16:16 GMT approximately one hour after the event. In addition, the topic became a trend with 78 occurrences in the second interval of data collection after the first post, i.e. at 16:30 GMT.

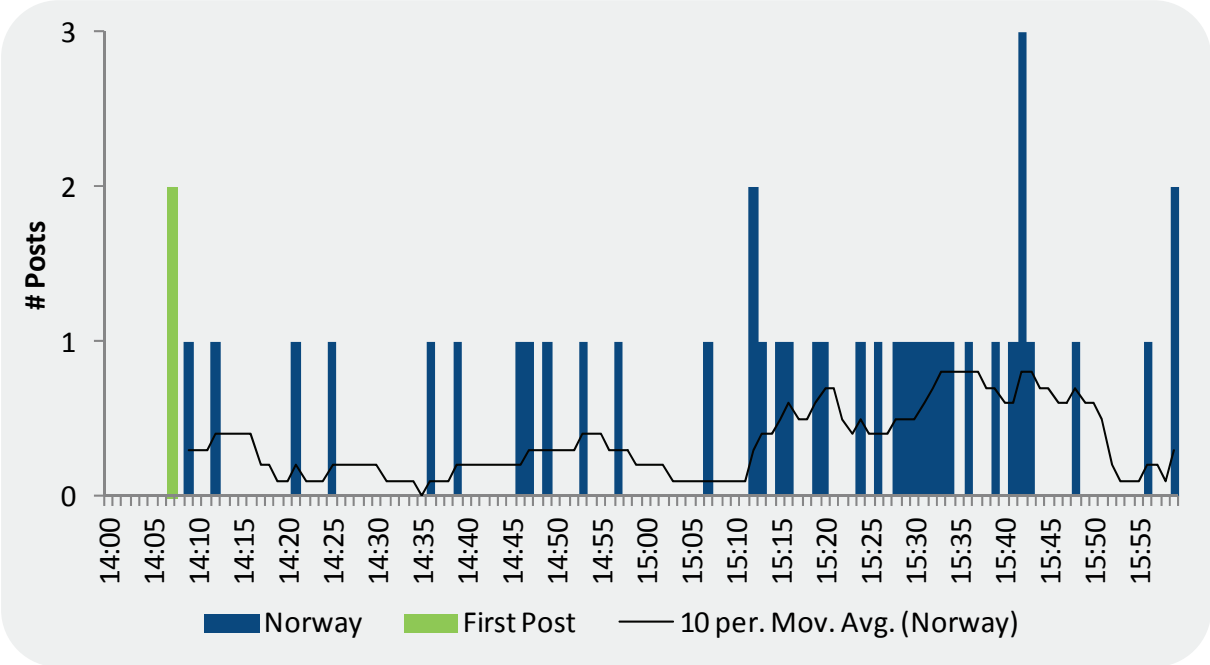

Figure 20: Information diffusion for disruptive event "Norway"

When it comes to the events in Norway, the situation is different. Regarding the time difference between the event and the first post it can be seen that the first post was shared a bit faster, approximately 50 minutes after the event. However, the spread of this topic significantly differs from the previous one. Posts are shared on irregular intervals and the number of posts is relatively low with an average below 1 post per 10 minutes. This illustration clearly explains why this topic positioned itself very low on the weighted topic group list.

Based on these two examples a similarity can be seen in the fact that both topics appeared on Facebook relatively fast, however, the example with Norway clearly illustrates that *disruptive events* not necessarily become trending topics, even in case of such events that are attracting a lot of attention on other, more traditional sources of media, such as television or radios.

5.5. Discussion and Managerial Implications

Apart from providing contribution for the field of text mining, this study provides a contribution for marketing practitioners. The methodology proposed in this section provides the possibility for brand image monitoring by overcoming the challenges of simple "buzz" monitoring based on the keyword search, which could lead to inaccurate results due to the possibility that the

keyword might appear in a totally unrelated context. Thus the following implication can be drawn:

> *I1: Companies utilizing Facebook for marketing purposes should perform trend monitoring over public posts which in turn enables accurate image monitoring.*

In addition, trend monitoring provides the possibility to extract the meaningful topic groups, for example, discussion over a particular product, which could further be subjected to sentiment analysis to estimate the perception of this product, without the need for timely manual text analysis or costly user surveys. Therefore:

> *I2: Companies utilizing Facebook for marketing purposes should perform trend monitoring over public posts which in turn enables cost efficient market research without the need for time and money consuming user surveys.*

Moreover, the results of the trend monitoring represent a source of ideas for content referring to external events which might be posted on the SMM channel. Still, the analysis over the characteristics of the recognized trend categories showed that topics which attract a lot of attention in traditional media might not receive so much attention on social media platforms. For example, the topic of Norway did not become a trending topic indicating that this might not be a suitable choice for event to be mentioned on the brand page. Thus a recommendation can be given:

> *I3: Companies utilizing Facebook for marketing purposes should perform trend monitoring to gain insights into the popular topics referring to external events (suitable for social media platforms), which could be communicated to the fans in order to increase the level of engagement over their SMM channels.*

In turn, Amy Winehouse or Harry Potter attracted great volume of posts. In addition, Harry Potter was trending over a long time period. This indicates that this topic might also attract the attention of the Facebook brand page fans for a longer period of time, and as such it might be used as a topic related to a contest organized on the brand page, offering for example movie theater tickets as award, which was also found to be a commonly used form of content (see Chapter 7: “Customer Engagement on Facebook Brand Pages” for details). Based on this reasoning the following implication can be formulated:

> *I4: Companies utilizing Facebook for marketing purposes should perform trend monitoring to gather ideas about topics which are popular over longer period of time and which could be used as a basis for organizing contests on their SMM channels in order to increase the level of engagement.*

Finally, the results showed that Facebook users frequently refer to daily routines, and that these posts have regular temporal patterns. Thus, even such simple content created at appropriate time might increase the engagement on the Facebook brand page. Thus the final implication would be:

> *I5: Companies utilizing Facebook for marketing purposes should perform trend monitoring to gain insights into the temporal patterns of commonly referred topics, such as daily routines, which could be used to select an appropriate time of posting, in order to increase the level of engagement over their SMM channels.*

5.6. Summary, Limitations and Future Work

This chapter presents a system for trend detection over the Facebook public focusing on two problems: (1) data collection and (2) trend detection. The proposed data collection algorithm provides the possibility to collect large datasets despite the existing Facebook privacy policies. An evaluation on whether the amount of collected data is a representative sample for the content shared on Facebook was not performed. Instead, the goal of this study was to confirm that Facebook can be used as an additional valuable source of information regarding the topics that attract the attention of a large fraction of people.

In addition, an analysis of the obtained dataset was performed to determine the structure of the public Facebook posts in terms of the: (1) length, (2) language, (3) post media type and (4) posting distribution over the time of day. Based on the obtained results from the dataset analysis, an algorithm for trend detection over Facebook public posts was proposed which (1) takes in consideration only *status* posts present within 84% of the dataset, (2) does not consider multilingualism due to the fact that English language is used in 78% of the posts, and (3) limits the minimum length of the n-gram based terms to 2 in order to avoid noise and improve performance.

Based on the preliminary evaluation and the previously presented discussion a conclusion can be made that this simple approach performs well only on certain topic groups. In particular, the applied clustering algorithm was found

to be very greedy, resulting in problems with topics where there is a little overlap between terms belonging to the same topic group and an existing overlap with the more dominant topic group of Amy Winehouse. Therefore, this algorithm needs to be further improved to achieve optimal results.

Further, the analysis of the results of the proposed trend detection algorithm, revealed the possibility to distinguish among three different categories of trending topics: (1) *disruptive events*, (2) *popular topics* and (3) *daily routines*. Based on the comparison of their characteristics it was shown that statistical measures, such as standard deviation, kurtosis and skewness can be used for distinction of *disruptive events* among the trending topics. In addition, the results confirmed that the information travels and spreads fast among Facebook users. Still, *disruptive events* do not necessarily become trending topics even in cases when they attract a lot of attention on more traditional sources of media.

Finally, implications of the presented findings were drawn from the perspective of marketing practitioners by pointing to the possibilities to use the proposed method for image monitoring, market intelligence and gathering ideas for non-brand related content communicated to the consumers on SMM channels.

Future research should focus on improvement of the proposed algorithm, in particular in the segment of clustering by applying more advanced methods. A possible approach could be a combination of named entity detection over the unigrams and Latent Semantic Indexing (LSI), LDA models, or network community detection. In addition, it would be interesting to test the implications provided for social media practitioners to see if the content referring to topics identified by monitoring trends on the platform has the potential to increase the engagement level on SMM platforms.

Summary of Main Findings

- Facebook can be used for trend extraction and as a news source since information travels and spreads fast.
- Trends on Facebook can be divided into (1) disruptive events, (2) popular topics and (3) daily routines.
- Data collection:
  - Facebook provides the possibility to collect public posts in near real-time mode through the search functionality of the Graph API.
  - Despite the privacy settings, a large datasets can be obtained, with more than 500,000 public posts per day.
- Trend detection methodology:
  - Simple approach of TF-IDF yields satisfactory results for topic identification and trend monitoring on Facebook.
  - Descriptive statistical measures can be used for distinction of disruptive events among the trending topics.
- Trend monitoring provides the following opportunities to SMM:
  - Possibility for brand image monitoring by overcoming the challenges of simple “buzz” monitoring.
  - Possibility to perform market research by extracting the topic groups, e.g. discussion over a particular product.
  - Source of ideas for suitable content referring to external events.
  - Source of ideas for content used as a basis for organizing contests on the SMM channel.
  - Source of ideas for content referring to daily routines and the appropriate posting time.

6. Patterns of Interaction on Facebook Brand Pages

The value of SMM campaigns can be measured through the "amount of interaction and the richness of the interaction that consumer has with the good or service." (Parent et al. 2011, pp. 221) In addition, understanding the interactions on Facebook brand pages provides insights on how fans respond to different approaches undertaken by the companies on their SMM channels.

Interactions on social media platforms can be characterized by the conversations driven by the consumers. Therefore, increasing the level of interaction would lead towards increased volume of UGC and WOM communication. Since WOM communication was found to be a powerful tool for increasing the brand awareness (Godes and Mayzlin, 2004; pp. 545-560) and attitude (Liu 2006, pp. 74-89), focusing on the characteristics of the target audience would enable selection of a suitable form of relationship with the fans. Therefore, companies should build their SMM strategies starting from the results of interaction analysis over the members of their online brand communities (Li 2007b).

The study presented in this chapter addresses the research questions RQ6: "What are the interaction patterns on social media platforms?" and RQ7: "What are the characteristics of the social network created between the users of social media platforms?" presented in Chapter 1.2.1.2: "Users of Social Media Marketing Platforms". It proposes a categorization of users based on their interaction patterns and explains the structural characteristics of the social network on Facebook brand pages.

This study was originally published as: "Understanding the user generated content and interactions on a Facebook brand page" (Pletikosa Cvijikj and Michahelles 2013). This section contains excerpts from the referenced publication which will not be further demarcated in the text.

6.1. Introduction

The most general user categorization on online platforms distinguishes between participants who create content, i.e. *posters*, and those who might read the content but do not post, i.e. *lurkers* (Nonnecke and Preece 1999, pp. 123-128). As such, this categorization is very general and does not account for differences in interaction possibilities on individual social media platforms.

In order to extend these two main groups into categories which would provide greater level of details, scholars have addressed the problem of user categorization on online platforms, resulting in variety of categorizations due to different platforms and approaches. A survey of existing categorizations pointing to the connections between them, as proposed by Brandtzaeg and Heim (2011, pp. 45), is given Table VII.

Table VII: A survey of existing user categorizations (Brandtzaeg and Heim 2011, pp. 45)

Brandtzaeg and Heim (2011)	Kozinetz (1999)	Nielsen (2006)	OFCOM (2008)	Rogers (2003)	Justification
Socializers	Minglers	Intermittent Contributors	Faithfuls	Early majority	Open to new ideas, active and influencing in SNs
Debaters	Devotees	Intermittent Contributors	Functionals	Early adopters	Early adopters with interest in UGC
Lurkers	Tourists	Lurkers		(Late majority)	Use SNs for lurking or time-killing
Sporadics			Alpha socialisers and followers	Late majority (and laggards)	Newcomers and sporadic users
Actives	Insiders	Heavy contributors	Attention seekers	Innovators and early adopters	Advanced and frequent users

Apart from scholars, practitioners are also interested in providing a categorization scheme which would explain the interactions on social networks. For example, a popular categorization was proposed in a study

conducted by Forrester, under the term “social technographics” (Li 2007b). This categorization distinguishes among six levels of participation: (1) *creators*, (2) *critics*, (3) *collectors*, (4) *joiners*, (5) *spectators* and (6) *inactives*. A short description of the activities performed by members of each of the proposed categories and a summary of the results obtained in the Forrester’s study in terms of level of participation among adult users of online platforms from North America are provided on Figure 21.

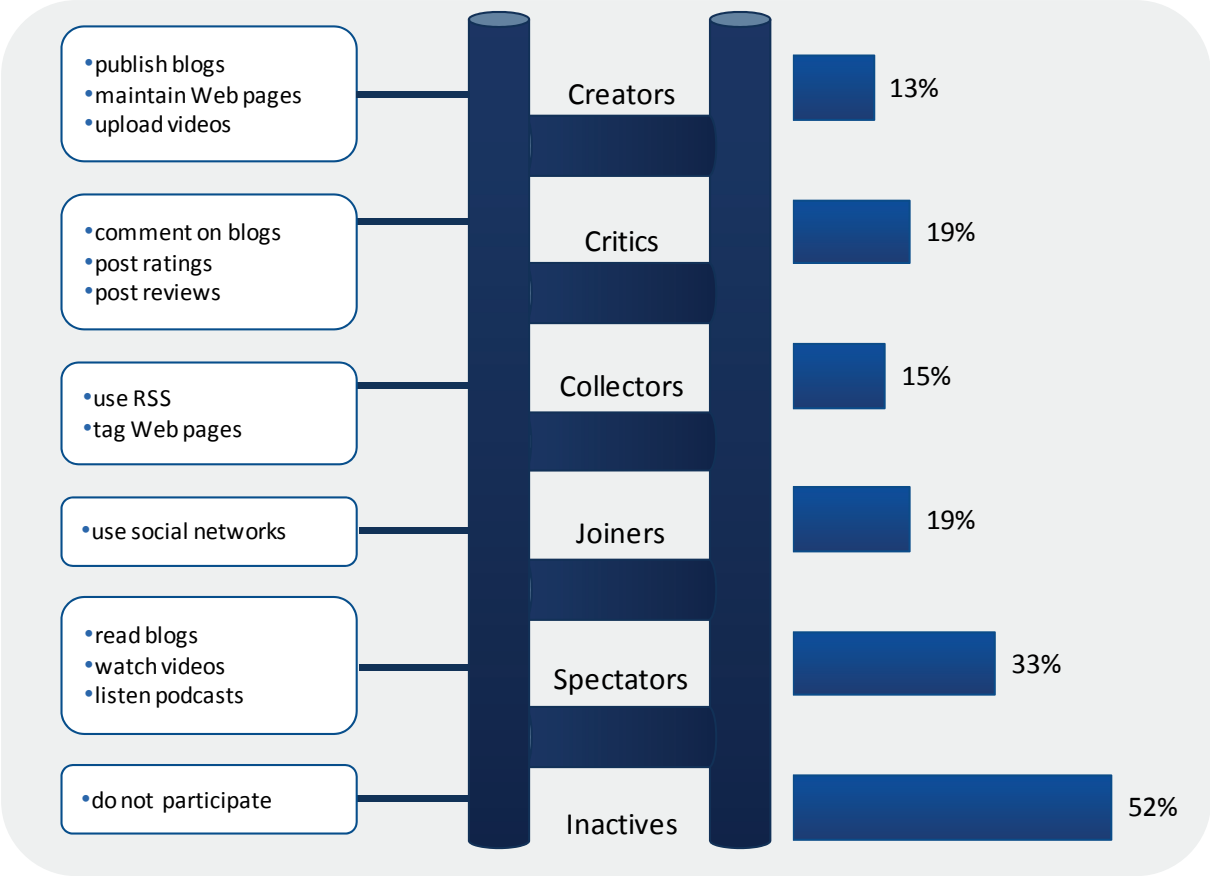

Figure 21: Social technographics ladder (Li 2007b)

The drawback of social technographics approach is that it places all users of SN platforms under the same category - *joiners*, thus taking in consideration only the initial action of joining the SN. However, it does not provide details on different interaction possibilities after joining the SN.

Finally, looking at the interactions on social media platforms, with a goal of distinguishing among different levels of participation which lead towards creation of different forms and volumes of UGC, Parent et al. (2011, pp. 219-229) propose the following categorization: (1) *viewing*, (2) *forwarding*, (3) *commenting*, (4) *creating*, (5) and (6) *arbitrating*. An illustration of the hierarchical order of the proposed participation levels is given on Figure 22.

Figure 22: Levels of participation on social media (Parent et al. 2011, pp. 219-229)

Apart from providing a categorization, some studies have addressed the problem of understanding the users on the level of individual participants. Still, specific Facebook privacy policies, which allow access to profile information only to user's friends, introduce challenges to this approach. To overcome this problem, some studies used surveys and questionnaires (Joinson 2008, pp. 1027-1036; Lampe et al. 2006, pp. 167-170), while others collected profile and interaction data using Facebook crawlers (Gjoka et al. 2008, pp. 31-36; DiMicco and Millen 2007, pp. 383–386). Analysis of the fans on individual level provides the possibility to understand and approach the most influential fans whose actions would result in highest level of message propagation.

This chapter provides twofold contribution towards understanding the user interactions on Facebook brand pages. First, a new categorization is proposed, suitable for the available interaction modes on Facebook brand pages. In addition, a longitudinal exploratory study was performed to understand the level of participation over different categories. Finally, a social network analysis was performed to understand the interactions between the fans and the moderator, with a focus on the effect of the community size over the level of interactions.

The continuation of this chapter is structured as follows. Section 2 describes the used methodology. Section 3 presents the results of the analysis, while Section 4 discusses the findings and proposes implications for SMM practitioners. Finally, Section 5 provides a summary, discussion on the limitations of this study and proposes ideas for future work.

6.2. Method

The method applied in this study consists of two elements: (1) theory extension by proposing a new user categorization for the domain of a Facebook brand page and exploratory study of the interaction patterns of the fans belonging to the proposed interaction categories, and (2) analysis of the structure and evolution of the social network created as a result of interactions between the fans. The continuation of this section describes the details of the used approach and the dataset characteristics.

6.2.1. Dataset

Collection of the data for this study was performed using the customized Java tool, based on the Facebook Graph API, as described in Chapter 3.4: "Available Data Sources on Facebook".

The dataset used for this study consists of posts shared on the ok.- Facebook brand page (see Chapter 1.4.2: "Fast-Moving Consumer Goods as a Product Category" for details). The data collection was employed from March 2010 to March 2011. From the total of 759 posts shared on the ok.- brand page during the selected period, 134 posts were published by the page moderator, and the remaining 625 by the fans.

6.2.2. Data Analysis

The research method applied for understanding the interactions between the users and the moderator on the ok.- brand page is social network analysis (SNA). The goal was to understand the evolution of the interaction network, as well as the dependency between the interaction characteristics and the size/maturity of the community, i.e. total number of fans. For that purpose a dynamic social network analysis (DSNA) was employed, based on the utilization of the tool Condor[48]. DSNA provided the possibility for temporal visualization of the network structure and measures, i.e. visualisation of the network evolution over time (Gloor et al. 2004).

To describe the characteristics of the interaction network, the following measures from the SNA theory were applied (Wasserman and Faust 1994):

- *Betweenness centrality* is a measure of node's centrality, determined by the number of shortest paths between other nodes it belongs to. As such this measure indicates node's importance to the network. Nodes with high betweenness centrality represent bridges between separate sub-networks, thus enabling information flow between two parts of the network that would otherwise be disconnected.

- *Degree centrality* is a number of direct ties a node has, indicating the level of interaction the node has with other nodes from the network. Nodes with high level of degree centrality are those that are very active in the network and as such they represent "hubs", i.e. these nodes are

[48] Condor. http://wiki.soberit.hut.fi/virtualbrownbag/tiki-index.php. Accessed 2012-07-11

influencers in the network enabling information flow to high number of other nodes.

When applied to the network as a whole, centrality measures are commonly referred to as a network centrality or centralization. Network centrality quantifies the "tendency of the single point to be more central than all other points in the network." (Freeman 1979, pp. 227) 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' behaviour is. High values of network centralization occur when the network is dominated by one or a few very central nodes. The drawback of this situation is that once these central nodes are removed, the network breaks into unconnected sub-networks. Thus, highly central nodes represent points of failure.

Apart from centrality, an additional measure that provides insights into the structure of the whole network was used, i.e.:

- *Group density*, representing 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.

The network elements, i.e. nodes and ties will be described later, once the related terminology has been defined.

6.3. Results

Interaction analysis over the ok.- brand page enabled (1) categorization of the fans based on the interaction patterns, (2) insights into the evolution of the level of interaction, and (3) understanding the effect of the community size/maturity over the structural characteristics of the underlying brand community. This section presents and discusses the obtained results.

6.3.1. Categorization of Fans Based on Interaction Patterns

User categorization on social media platforms (including Facebook), proposed by Parent et al. (2011, pp. 219-229), suggest six level of participation. Still, this categorization does not make a distinction between the participation of the page fans and the moderator, thus including the *moderating* and *arbitrating* in

the list. In addition, *liking* interaction possibility which builds the face of Facebook is not taken in consideration.

Since the focus of this study is to understand how fans interact on Facebook brand pages, the above categorization was slightly modified in order to address the previously elaborated issues. The reasoning is based on the available options for interaction on brand pages, i.e. fans can (1) *post* content on the wall, (2) *share* existing posts, (3) *comment* on existing post, or (4) press the "Like" button beneath the post, i.e. *like* the post. Based on this, for the domain of Facebook brand pages, the general categorization was modified into the following engagement categories:

- *Posters* - fans that engage by writing a posts on the wall of the Facebook brand page,
- *Commenters* - fans that respond to existing posts on a Facebook brand page by writing a comment for it,
- *Sharers* - fans that share the existing posts on their own profile pages, thus making the brand related content visible to their friends,
- *Likers* - fans that indicate interest in an existing post by pressing the "Like" button, and
- *Lurkers* - passive fans that joined the brand community at some point, but never undertook any form of active engagement.

It should be noted that the sharing activity was not provided by the Facebook platform during the observed period, thus sharing information was not available for this study.

Facebook fans can clearly belong to more than one class, i.e. they can engage on the Facebook brand pages by performing more than one action over the time. For analysis purposes the highest engagement class was assigned. For example, if a user engaged by liking a post, but also by writing a comment, he was categorized as being a *commenter*.

Figure 24 illustrates the distribution of fans over engagement classes.

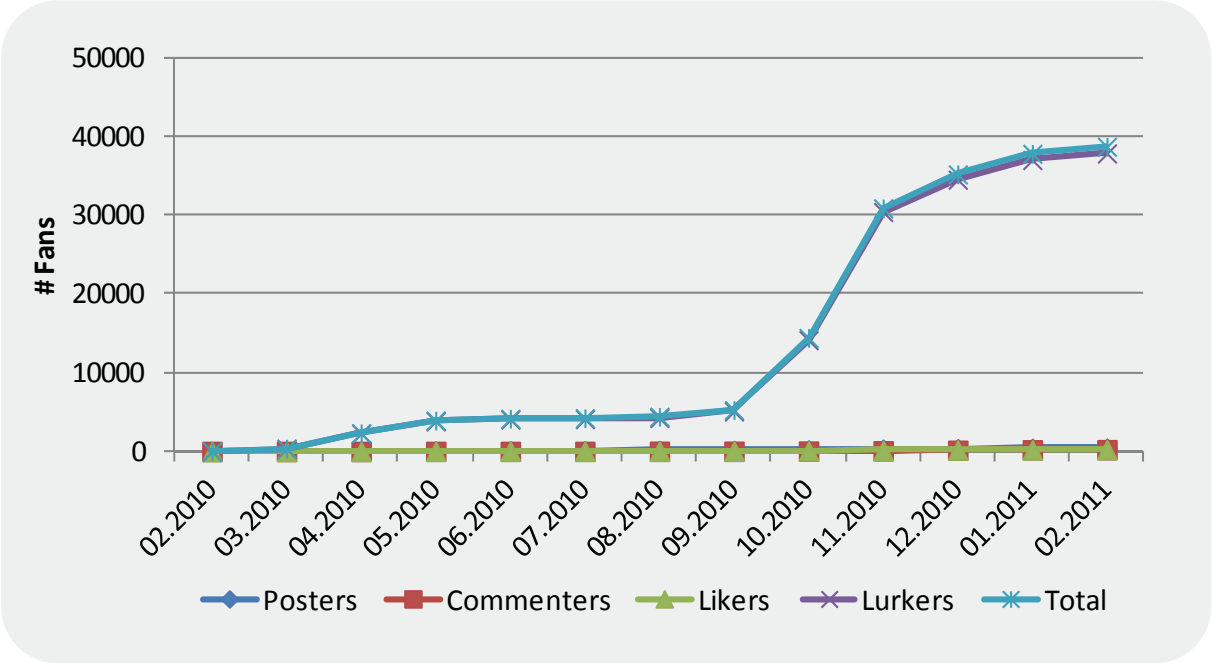

Figure 23: Distribution of fans over engagement classes and the total number of fans

It can be seen that *Lurkers* represent majority of the fans on the analysed Facebook brand page. These results generally comply with the previous studies on participation inequality on social media platforms (Brandtzaeg and Heim 2011, pp. 28-51). Still, at the end of the observed period lurkers represent 98% of all fans, which is high compared to the 90% predicted on online platforms (Nonnecke and Preece 2000a, pp. 73-80).

To gain an understanding of the behaviour of active fans, an additional illustration is provided on Figure 24, by leaving out the *Lurkers* for better visualisation.

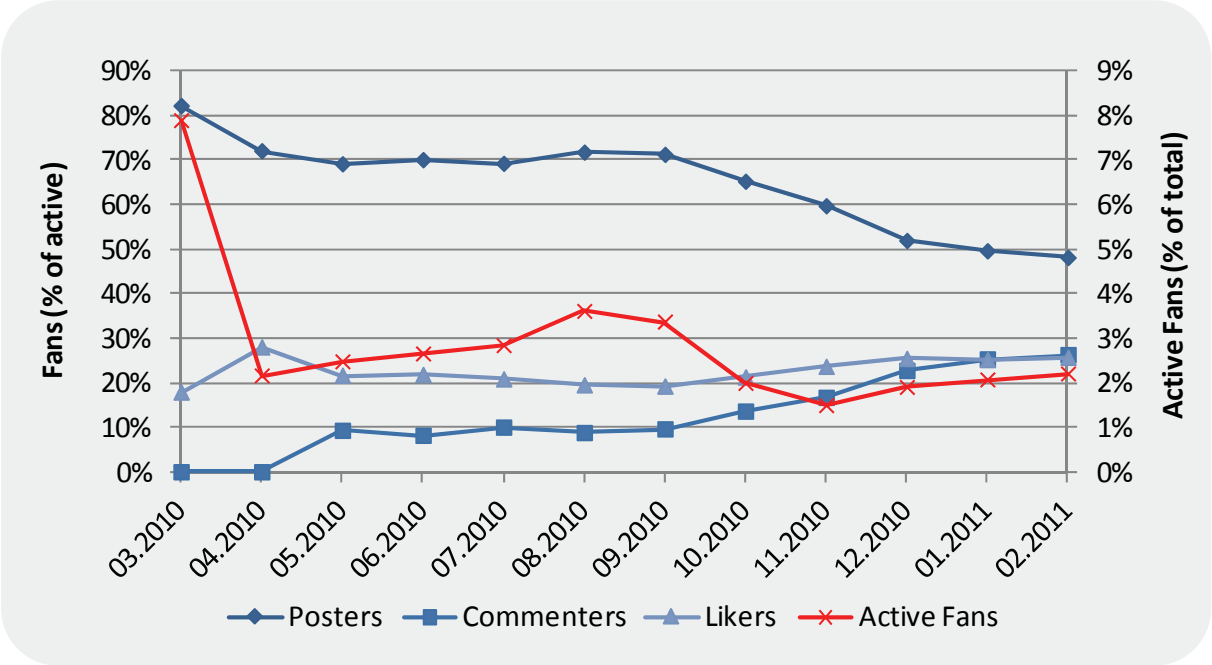

Figure 24: Number of active fans as a proportion of total number of fans (right axis) and individual classes of fans as a proportion of active fans (left axis)

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 is 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%, through 9% in June 2010, at the end of the study the *commenters* have reached the number of 26% of the active users. In case of *likers*, the numbers did not show large variations, ranging between 18% and 28% of the active users.

These results comply 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). Moreover, in the domain of brand communities, participation in smaller communities was found to result in a stronger interpersonal relationships and a greater intention for social engagement (Dholakia et al. 2004, pp. 241-263). Thus, members of small communities are likely to be more connected to the brand community, which would results in higher levels of engagement.

6.3.2. The Evolution of Interaction Level

Previous analysis provided insights into the main modes of engagement on Facebook brand pages, but does not contain the full information regarding the level of engagement.

In order to understand if the same effect of the community size exists over the volume of actions undertaken by the fans, an additional analysis from the perspective of number of posts, comments and likes shared by the users was performed. In addition, since the number of fans changed significantly over the observed period, the number of posts, comments and likes were normalized with the number of fans. The obtained results are illustrated on Figure 25.

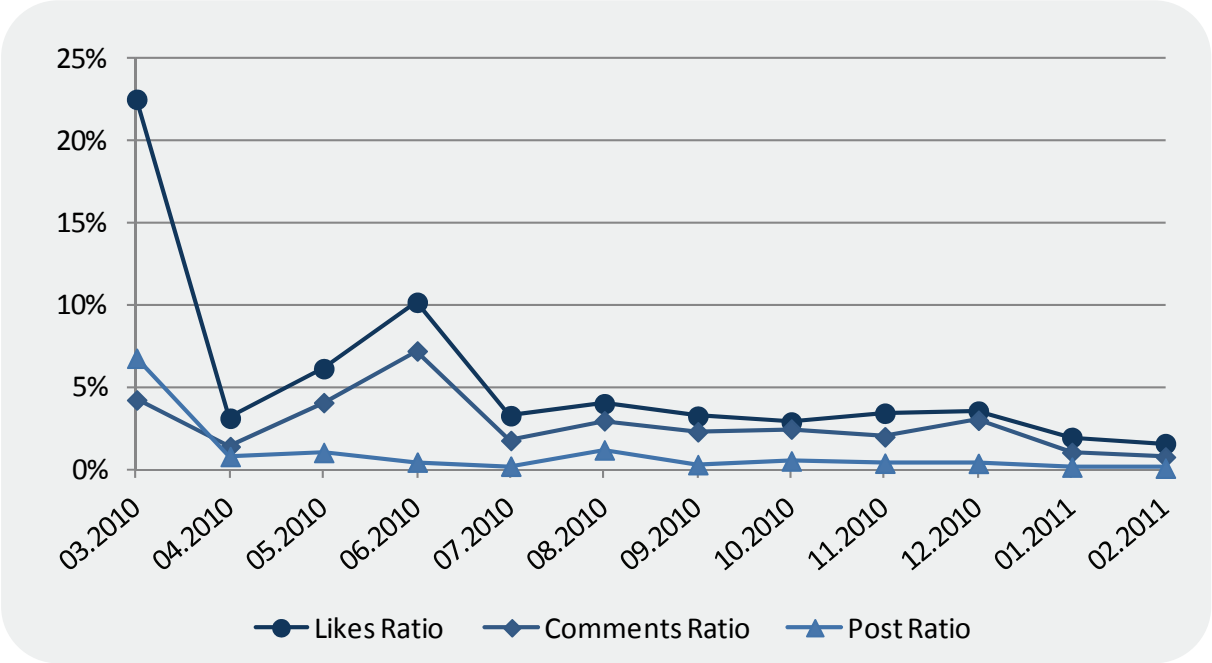

Figure 25: Number of likes, comments and posts from fans in relation to total number of fans

The results showed that after an initial peak in March 2010, the level of interaction fell down and remained almost constant until the end of the observed period.

The likes' ratio showed the highest values throughout the observed period. This indicates 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. On the contrary, the normalized numbers of posts show lowest values, which indicate that majority of fans don't feel free to share verbal opinions which might result in additional actions by other users or the moderator, such as comments.

Apart from the initial peak, an additional increase in the number of comments and likes can be observed starting from May 2010, with the maximum in June 2010. This period corresponds with two Facebook Ad campaigns organized by the company to increase the number of fans - first one on the week of April 15th and the second one in the week of May 25th. These numbers and the increase in the number of fans indicate that this action had positive outcome.

An additional measure for the interaction level can be obtained through the number of unique page views from the fans and non-fans. This measure can be obtained through a Facebook Insights platform which is provided to the page administrators in order to support them in high-level monitoring of the content and activities. Figure 26 illustrates the results in relation to the total number of fans.

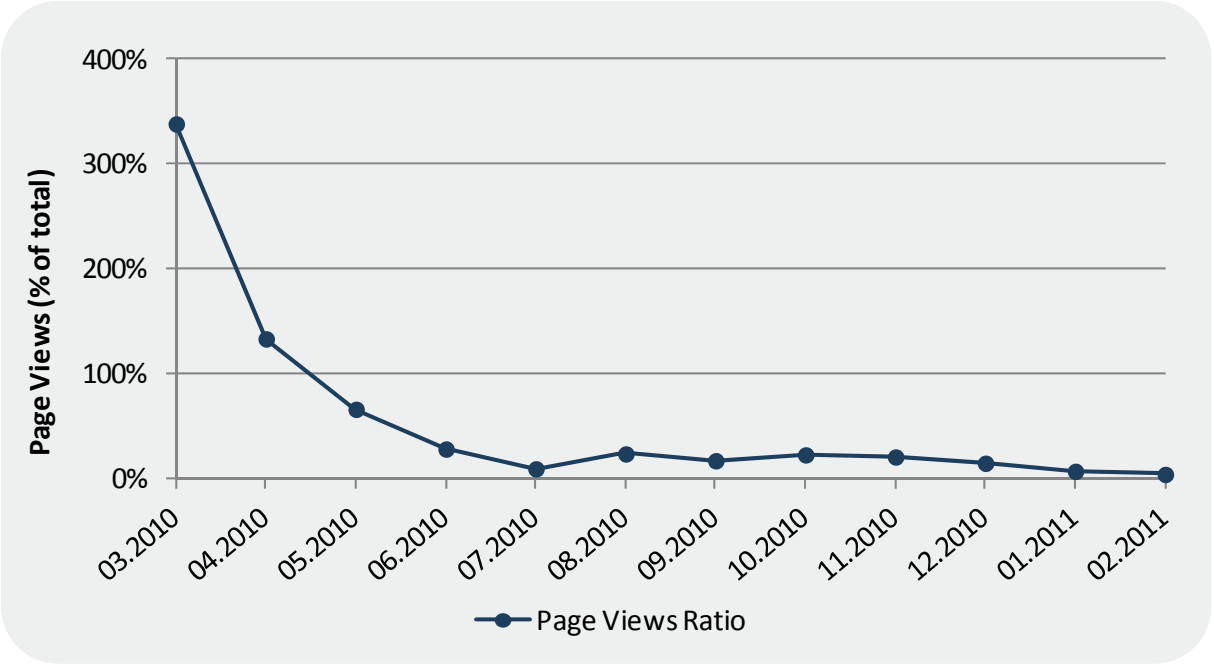

Figure 26: Number of page views in relation to the total number of fans

It can be seen that this measure also exhibits decrease over time. In addition, while at the beginning there were many page views by non-fans, as the brand page reached certain level of maturity, this number fell. An interesting observation is that the Facebook Ad campaigns did not result in increase of the page views, i.e. the peak visible on Figure 25 is not visible again. This complies with the previous findings which show that social media users avoid looking at the advertisement served on social media platforms (Ulusu 2010, pp. 2949-1957).

While the interaction of the active fans can be monitored, activities of *lurkers* remain unknown. Since page posts appear on fans' wall, *lurkers* don't need to

access the brand page in order to consume the content, thus leaving no measurable trace of their activities.

6.3.3. Structural Characteristics of the Interaction Network

A final overview over the interactions between the fans was obtained through a structural analysis of the interaction network. To create the interaction network fans were used as network nodes and commenting and liking activities as network ties. Furthermore, since liking and commenting activities previously exhibited different characteristics, these activities were again divided into separate networks to see if they exhibit different evolution over time. Thus for each post, a tie in the commenting network was created if there was a comment by connecting the *commenter* to the *poster*. In addition, within the liking network, for each like a tie was created from the *liker* towards the *poster*.

Posting activity was not taken in consideration since in the format provided by the Graph API all posts shared by the users are addressed to the moderator, thus the resulting network has a perfect star shape and as such provides no insights.

The resulting social network representing the commenting activity is illustrated on Figure 27. This illustration clearly shows that the page moderator, represented with the green square, plays a central role within the commenting network. This means that his activity within the network is essential for increasing the level of engagement on the Facebook brand page.

Figure 27: Structure of the commenting network between the moderator and the fans

In addition, we looked into the structure of the liking network represented on Figure 28. It can be seen that this network is bigger and more complex compared to the commenting network, confirming again that fans engaged the most by liking the content on the Facebook brand page. In addition, apart from the moderator, there is one more node with high centrality, represented with the red triangle.

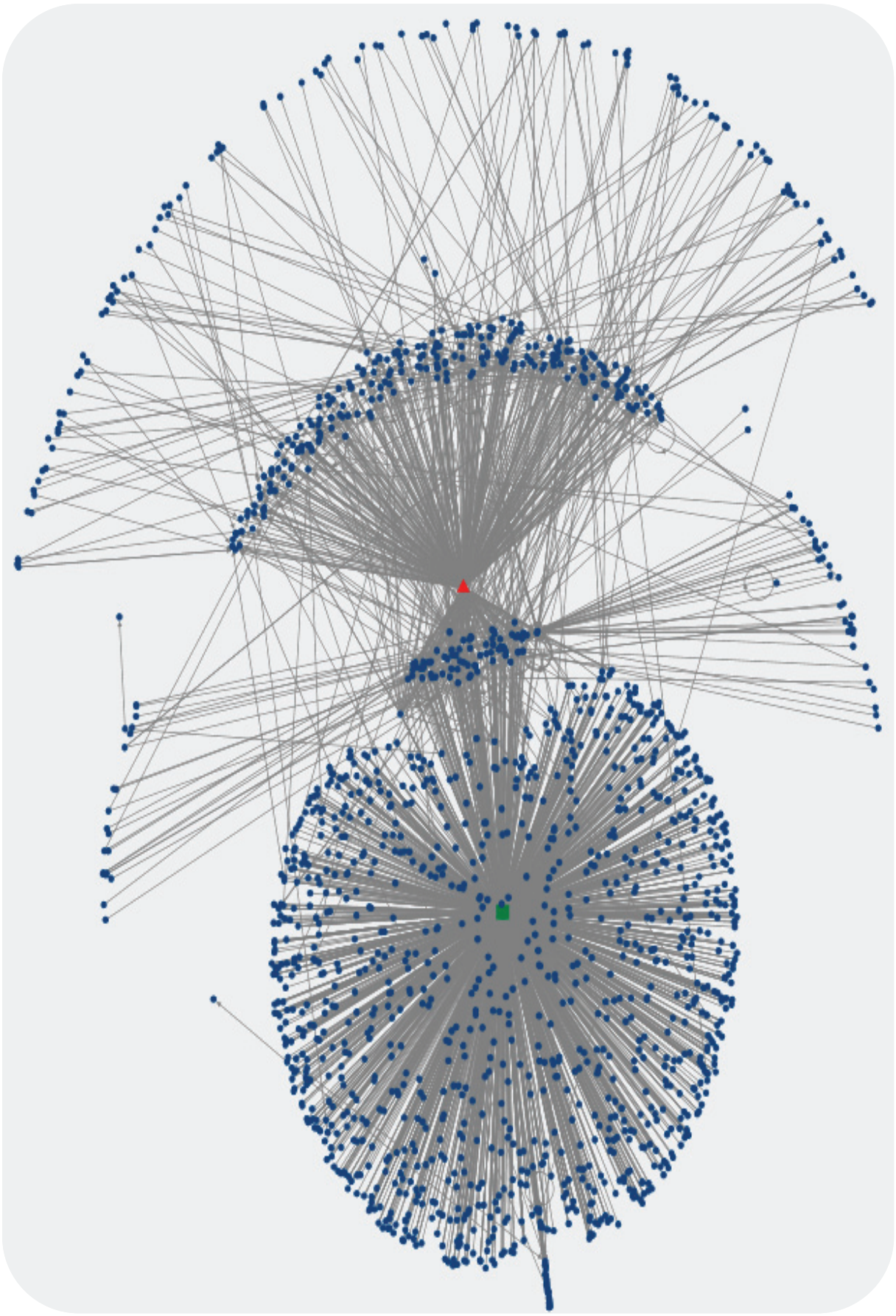

Figure 28: Structure of the liking network between the moderator and the fans

To observe if the similar effect of the network size exists over the structural characteristics of the interaction network, the method of DSNA was applied over the selected period.

The results obtained from DSNA over the commenting network are illustrated on Figure 29.

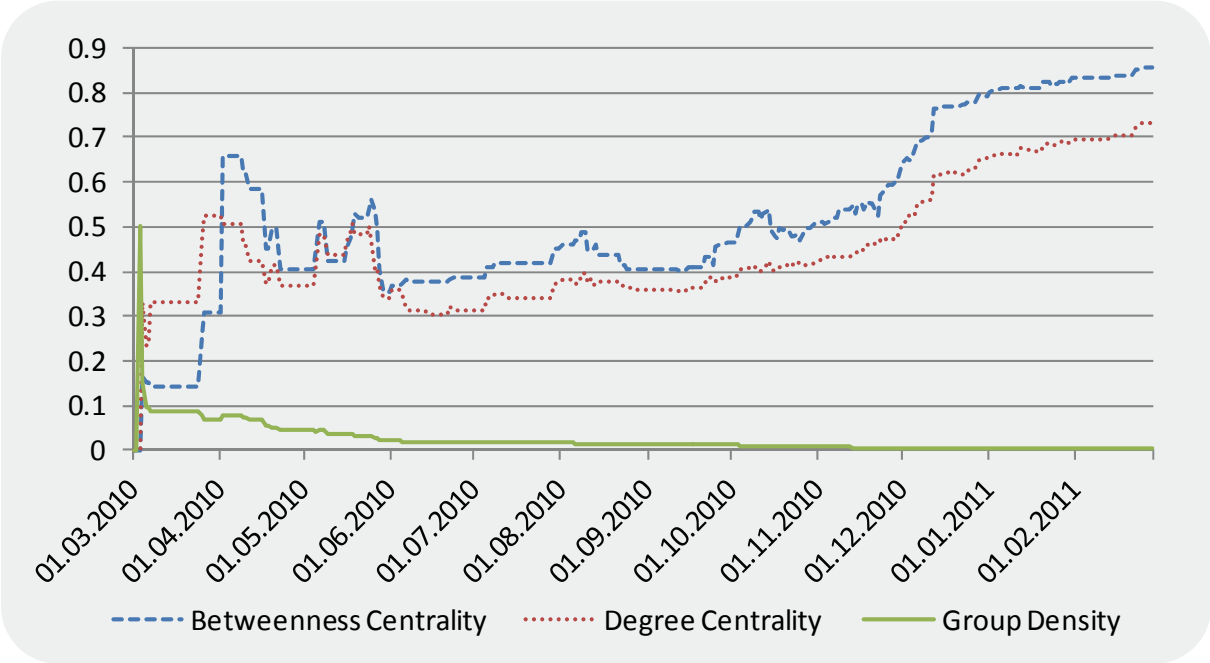

Figure 29: Betweenness, degree centrality and group density of the commenting network (with the page moderator)

Figure 29 shows that the group density exhibits initial peak in March 2010, then falls down and continues into a relatively stable phase. On the contrary, both centrality measures follow similar patterns of increase over time. This shows that there are significant differences in the way fans engage on the brand page. While some fans are active writing comments, others do not engage with a great intensity.

Since the commenting network represented on Figure 29 includes activities from both, fans and the page moderator, based on the network structure illustrated on Figure 27, an assumption was made that the obtained results might be biased by the page moderator. For that reason, all comments from and to the page moderator were filtered out from the social network. The obtained results of the commenting network only among the fans are shown on Figure 30.

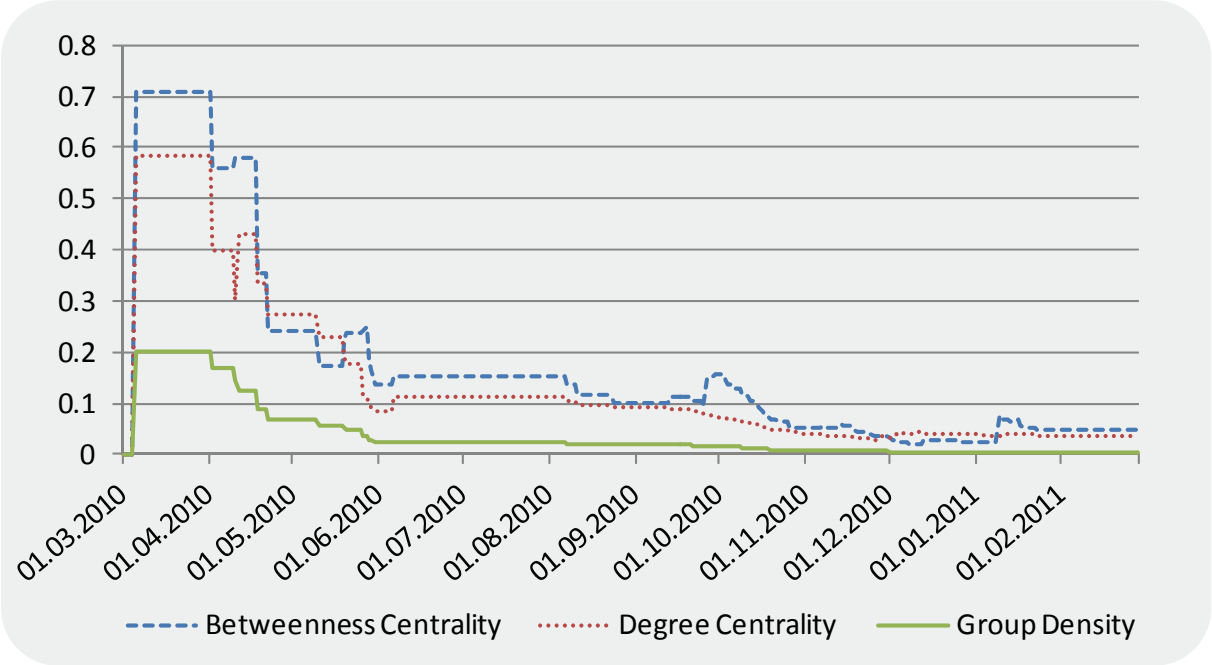

Figure 30: Betweenness, degree centrality and group density of the commenting network (without the page moderator)

It becomes clear that commenting interaction between the fans decreases over time. After the initial peak, both interaction measures decrease until June 2010, followed by a relatively stable period until October 2010, where an additional decrement can be seen before entering into the stable behaviour. Compared to the total number of fans illustrated on Figure 23, these fluctuations are exactly the opposite, confirming again the negative effect of the network size over the interactions between the users.

In terms of liking, the results of the DSNA, revealing the evolution of the characteristics of the interaction network are illustrated on Figure 31.

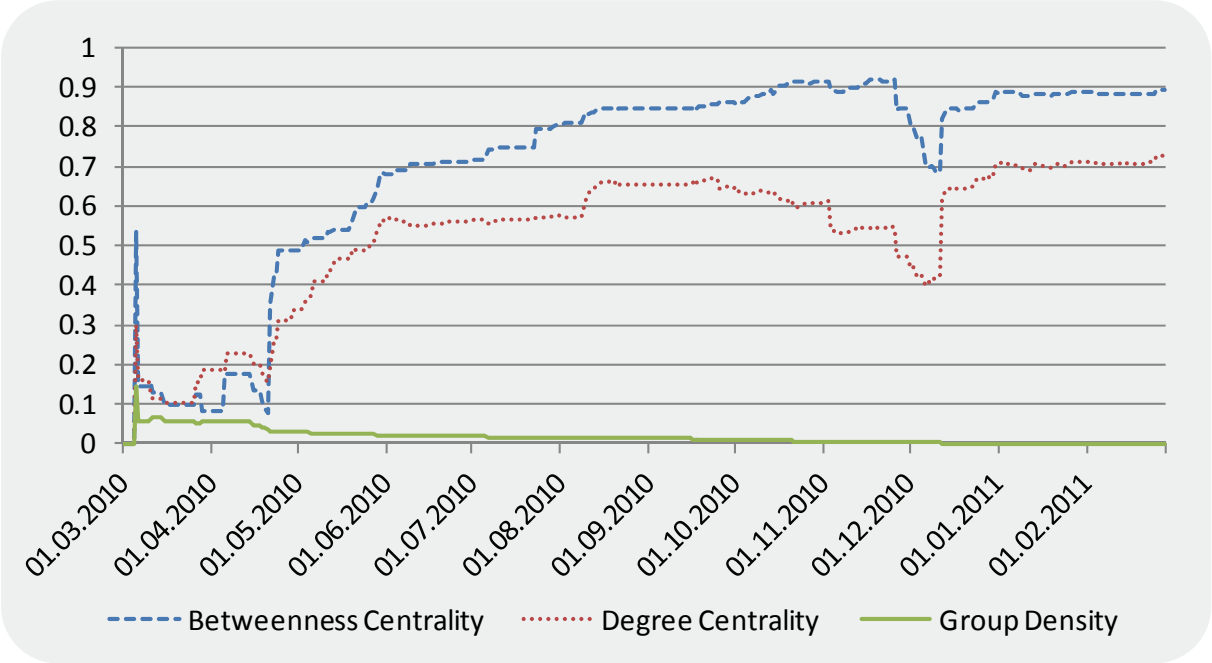

Figure 31: Betweenness, degree centrality and group density of the liking network (with the page moderator)

While the group density of the liking network presented on Figure 31 shows similar behavior, the distribution of centrality measures differs. On overall level, an increase is present again, with a negative peak in December 2010. This period corresponds with the period when a mobile phone line was launched which had some problems at the beginning. This has caused a flow of Criticism & Complaints posts as already mentioned in the Chapter 4: "User Generated Content on Facebook Brand Pages". After the problems were solved, the communication returned to its "normal" form.

To compare if the same difference between the interaction dynamics can be observed when the moderator is removed from the network, the same filtering was performed as before. The resulting network dynamics is shown on Figure 32.

It can be seen that in the case of liking, the behaviour of users resembles the behaviour of the network in whole. This means that while some fans frequently like the content shared by other fans, others only occasionally or never engage. This result complies with the observed structure of the liking network (see Figure 28).

Further, looking at the "critical" period in December 2010, it can be seen that the same effect is not visible. This clearly indicates that the previously observed difference originates from the actions undertaken by the moderator, who was unlikely to "like" the posts containing the complaints.

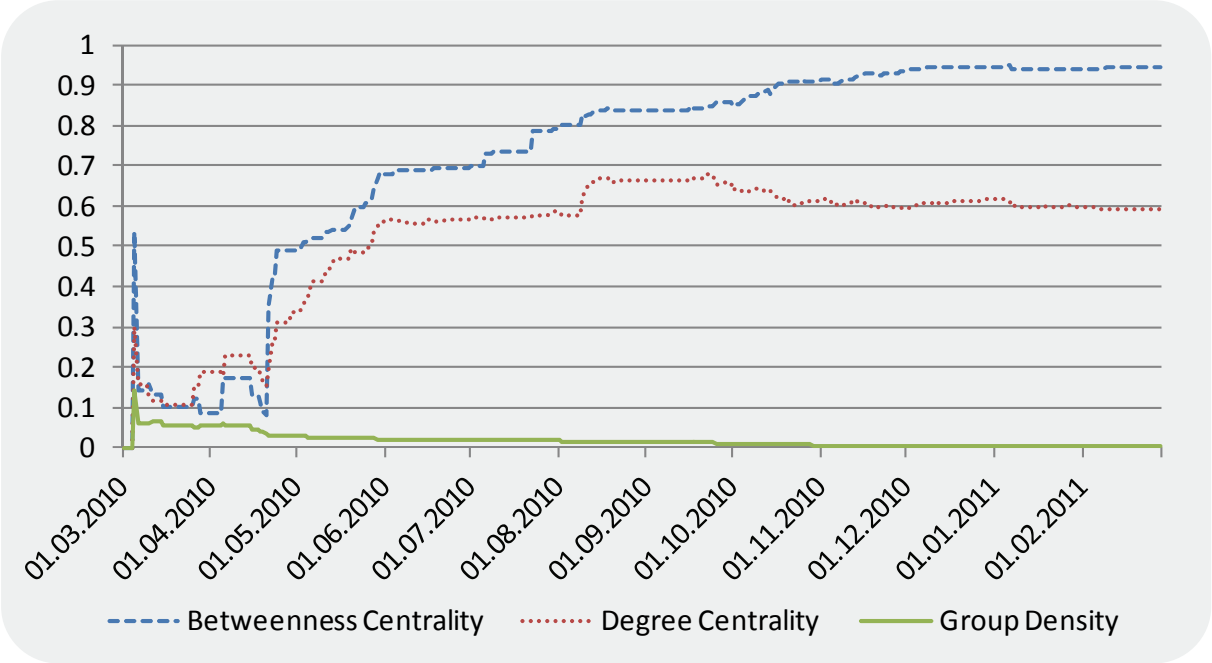

Figure 32: Betweenness, degree centrality and group density of the liking network (without the page moderator)

6.4. Discussion and Managerial Implications

Previously presented results show that Facebook provides a possibility for user categorization based on the activities available to the fans. This categorization is important for the companies in order to understand how their customers use the social media platform, in order to develop appropriate communication strategies. Continuous monitoring of the activities based on the proposed categorization enables deeper understanding of the level of interactions and its evolution over time. The results presented in this chapter show that majority of the brand page users (98%) are passive users, i.e. *lurkers* and that this group grows with the growth of the community. Summarized in a form of managerial implication, this would mean that:

> *I1: An appropriate approach should be undertaken by the company to increase the level of interaction among the fans which would ultimately result in a lower number of lurkers who represent 98% of the fans.*

Different interaction patterns, undertaken by the fans on the Facebook brand page, result in different form of UGC. Posting and sharing are preferable actions since they generate a story in the news feed of the fan's friends and on his profile page, thus extending the reach of the marketing message. In case of liking and commenting, only a short notification appears in the friends' *ticker*, i.e. a small content frame which, might be shown (depending on the

preferences) on the right side of the news feed and is continuously updated with actions undertaken by the fan's friends. Thus the probability of exposing additional Facebook users to the brand related content is significantly reduced. Still, our study showed that active fans prefer not exposing themselves to possible reactions from other members of the community, thus embracing the "safest" option for interaction, i.e. *liking*. Thus, the following implication can be drawn:

> *I2A: An appropriate approach should be undertaken by the company to address different classes of users in order to lead them towards the higher level of interaction which could ultimately result in a higher level of brand awareness and growth of community size.*

Previous findings showed that daily users exhibit significantly more interest in brand profiles (Li 2007a), and that triggering the user interaction could result in optimization of the marketing investment (Sterne 2008). Therefore, improving the level of user's activity is a worthy goal for the companies and the following recommendation can be given:

> *I2B: Stronger moderation, such as encouraging posters by their content and preventing or discouraging aggressive posts and comments, could lead towards increased interaction frequency.*

The proposed approach also provides the possibility to identify influencers, i.e. the "superfans". Companies should devise a plan to address them directly, since these are the "customers who are so positive about a brand that they do much of its marketing and sales themselves – and for free" (Harris and Rae, 2009, pp. 31). Thus we suggest:

> *I3: A strategy that would provide the possibility to directly approach the influencers on Facebook brand pages could lead to increasing the reach of the marketing message.*

Finally, the DSNA showed that Facebook brand pages exhibit similar interaction evolution as already recognized in the sociology research, i.e. as the community grows, the percentage of active users reduces and the interaction becomes uniform. Furthermore, the moderator becomes a central figure in the network which influences the overall network structure. Since by definition a community assumes existence of a group of people interacting together, our results show that the brand communities on Facebook do not comply with the expected behaviour. While users interact with the moderator, the interaction between users themselves is relatively limited. This is an indication for the company that the increase of the size of the community requires more active

moderation in order to encourage creation of relations between the fans. Therefore, the final implication would be:

> *I3: A strategy that would incorporate activities such as competitions, polls and discussion threads, could stimulate creation of social ties and interactions among the fans, thus overcoming the problem of the negative effect of the community size over the interaction level.*

6.5. Summary, Limitations and Future Work

This study presents an analysis of the interactions between the users on a Facebook brand page. A classification scheme was proposed based on the engagement patterns of the fans and a longitudinal analysis of the interactions among fans was performed. Based on the obtained results implications for social media marketing were drawn.

The main limitation of this study is a relatively small dataset extracted from only one Facebook brand page. Still, the longitudinal approach provided the possibility to gain more insights and to observe the correlation between the community size and the engagement level and characteristics.

In addition, during the observed period, the sharing activity on Facebook was still not provided to the fans by the platform itself. Thus analysis of this group of participants on Facebook brand pages is still outstanding.

The analysis presented in this paper can be used by marketing practitioners as a measure for successful social media marketing utilization over time. Automation of the proposed methods would provide the possibility for real-time monitoring and timely reaction. This could be achieved by integration of the script used for data collection, implementing a simple logic for user categorization and an existing DSNA tool. Details of the proposed automation are presented in Chapter 9.3.1: “User Analysis”.

Summary of Main Findings

- Facebook provides the possibility for categorization of fans based on the interaction patterns: (1) *posters*, (2) *commenters*, (3) *sharers*, (4) *likers* and (5) *lurkers*.
- *Lurkers* represent the largest fraction of fans (98% at the end of the observation period)
- The number of active fans reduces with the growth of brand community.
- Facebook Ad campaigns are valuable tool for increasing the number of fans and interaction level on the page.
- Fans embrace *liking* of existing content as the most appealing form of interaction.
- The brand communities on Facebook do not comply with the expected community behavior, i.e. fans do interact between themselves.
- The page moderator is the central figure in the social network based on the interactions on the Facebook brand page.
- As the Facebook brand community grows, the level of interaction among fans reduces.

7. Customer Engagement on Facebook Brand Pages

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*[49] and *Return-on-Engagement* (Frick 2010) as new measures for success of SMM campaigns. In order to increase the level of customer engagement, companies need to build an engagement plan before diving into the SMM in order to appropriately approach their fans (Li 2007a). This could be achieved by finding out what interactions, content, and features will keep fans coming back.

The study presented in this chapter addresses the research question RQ8: "Which factors influence the level of engagement on SMM platforms?" presented in Chapter 1.2.1.3: "Engagement on Social Media Platforms". It undertakes an exploratory approach to reveal the specific content characteristics and posting time as factors that might influence the level of engagement on Facebook brand pages.

This study was originally presented as a case study in the publication entitled "A case study of the effects of moderator posts within a Facebook brand page" (Pletikosa Cvijikj and Michahelles 2011b, pp. 161-170). In addition, a similar study over 14 Facebook brand pages was published as: "The Effect of Post Type, Category and Posting Day on User Interaction Level on Facebook" (Pletikosa Cvijikj et al. 2011c, pp. 810-813). This section represents an extended version of the previous two publications, analyzing the engagement over 100 Facebook brand pages.

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[49] Introducing the New ROI: Return on Interaction. http://blog.emailexperience.org/blog/clickmail-marketing-at-eec/introducing-the-new-roi-return-on-interaction. Accessed 2012-07-17

7.1. Introduction

The change in the dynamics of marketing interchange between companies and consumers as introduced by SNs has placed a focus on the non-transactional customer behavior. In this new marketing era the terms engagement and participation became the central constructs capturing the non-transactional customer behavior used to describe the nature of participants' specific interactions and/or interactive experiences (Brodie et al. 2011, pp. 252-271; Kietzmann et al. 2011, pp. 241-251).

Consumer engagement on social media platforms can be explained by the "6C model", which illustrates the relations between (1) *Company*, (2) *Content* created by the company, (3) *Control*, (4) *Community*, (5) *Customers* and (6) *Conversation* among them (Parent et al. 2011, pp. 219-229). This model places the marketing related content as the central element that can be controlled by the company in order to increase the level of customer engagement, resulting in community participation and UGC. An illustration of the proposed relations is provided on Figure 33.

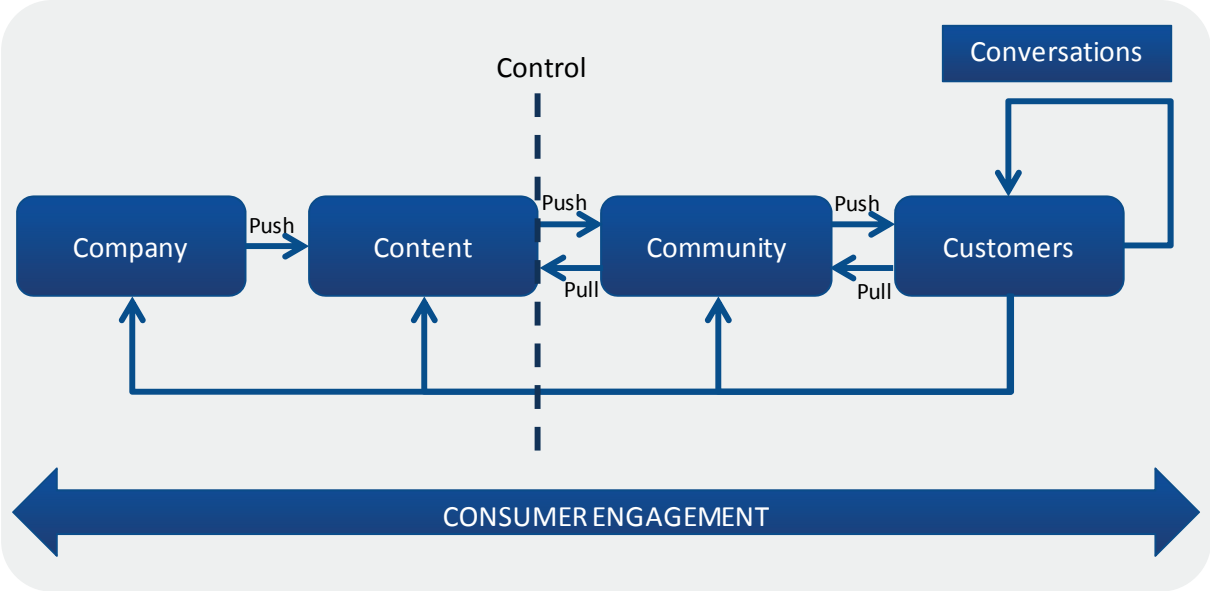

Figure 33: The 6C model of social media engagement (Parent et al. 2011, pp. 219-229)

In the context of Facebook, customer engagement over the content communicated by the companies on their brand pages could be measured through the number of undertaken actions such as likes, comments and shares. Each of these actions increases the reach of the marketing message by creating a visual trace on the wall of the Facebook fan, thus making the content visible to all of his social connections. Not only are active social media users influential within the underlying online platforms, but according to

Nielsen (2011) they are also influential offline. Thus triggering the user engagement on SMM platforms is a worthy goal for the companies which might optimize the marketing investment (Sterne 2010).

To contribute in the direction of finding out which factors increase the level of customer engagement on Facebook brand pages, this study focuses on two basic elements of the company's engagement plan:

- *Which content* should be posted to trigger higher level of engagement?
- *When* the content should be posted to trigger higher level of engagement?

To answer these questions, the following characteristics of the moderator posts were analyzed: (1) media type, (2) content type, (3) weekday and (4) time of posting. In addition, the level of customer engagement was measured through (1) the number of comments on individual post, (2) number of likes, (3) number of shares and (4) interaction duration.

The continuation of this chapter is structured as follows. Section 2 describes the used methodology. Section 3 presents the results of the analysis, while Section 4 discusses the findings and proposes implications for SMM practitioners. Finally, Section 5 provides a summary, discussion on the limitations of this study and proposes ideas for future work.

7.2. Method

The methodology used for this study represents an exploratory approach towards identifying the characteristics of moderator posts which might have an influence over the level of fan engagement on Facebook brand pages. The continuation of this section describes the details of the used approach and the characteristics of the used dataset.

7.2.1. Dataset

Collection of the data for this study was performed using the customized Java tool, based on the Facebook Graph API, as described in Chapter 3.4: "Available Data Sources on Facebook".

The gathered dataset consists of 5035 moderator posts obtained over the course of two months, from January to March, 2012, from 100 Facebook brand pages, selected based on the following criteria: (1) FMCG pages from the

Facebook page category: *Food/Beverages*, (2) "best players" within the selected category and (3) English language used for communication with the customers. The "best players" were identified through the Fan Page List[50] service which ranks the Facebook pages according to several metrics. For this study the number of fans was chosen as the relevant success criterion.

The complete list of selected pages and their high-level characteristics including (1) number of fans and growth over the observed period, (2) engagement over moderator posts and (3) engagement over UGC are provided in Appendix I.

7.2.2. Operationalization of the Variables

This section describes the reasoning behind the selection of the independent and dependent variables used for this study. First a definition of the independent variables, i.e. factors that might influence the engagement level is given, by providing a solution for categorization of the moderator posts. Then, a proposal is made for measures of customer engagement on a Facebook brand page, which are further used as dependent variables. Details of both steps are elaborated in the continuation.

7.2.2.1. Moderator Post Categorization

There are two basic elements that correlate to the posting activity of the moderator, as a part of the engagement plan: (1) *which content* should a moderator post on the wall to trigger more engagement, and (2) *when* the content should be posted.

In the most general way, posts shared on Facebook could be categorized by (1) the *media type* of the post and (2) the *topic* referred to within the post.

Post Media Type

Post media type corresponds to the actual *sharing* action undertaken by the page moderator within a Facebook page. At the time of writing, Facebook offers the possibility to share: (1) *status (ST)*, (2) *photo (PH)*, (3) *video (VI)* and (4) *link (LI)*. In addition, moderators can create (5) *polls*, by posing a question to the fans and providing a list of possible answers. Still, since the engagement possibilities over polls differ compared to those over other media types, i.e. polls can be *taken*, *followed* and *commented* on, for this study they were not

[50] Fan Page List. http://fanpagelist.com/. Accessed 2012-06-11

taken in consideration. Depending on the selected sharing action, Facebook assigns the corresponding media type to each post.

Content Categorization

Description of the content could be done by identifying the topics reflected in the posts. Since the classification of the posts into topics would result in too many groups, thus making the statistical analysis difficult, a content type can be used instead, further referred to as *content category*, as a more general topic representation. In order to assign the categories, a manual coding of the posts was performed, following the coding development strategy (Glaser and Strauss 1967). The categories assigned by the page moderator to the dataset used in a previous study were used as a basis for development of a coding scheme (Pletikosa Cvijikj and Michahelles 2011b, pp. 161-170). These categories include: (1) *Product Announcement*, (2) *Information*, (3) *Designed Question*, (4) *Questioner*, (5) *Competition*, (6) *Advertisement* and (7) *Statement*.

Table VIII: Summary of content categories assigned by the page moderator of the ok.-brand page (Pletikosa Cvijikj and Michahelles 2011b, pp. 161-170)

Post Category	Explanation	Example
Product(s) announcement	Announcement of new product launch.	*"4 neue ok.- Schokoladentafeln sind da!" (Original)* *"4 new ok.- chocolate bars are here!" (English translation)*
Information	Information regarding a sales location, number of page fans, etc.	*"Heute eröffnen in Egg und Altstätten zwei k kiosk Shops mit einer Auswahl an ok.- Produkten. Viel Spass beim Einkaufen!" (Original)* *"Two k kiosk Shops opened today in Egg and Altstätten with a selecion of ok.- products. Have fun shopping!" (English translation)*
Designed question	Posts in form of questions with a goal to engage users in a dialog.	*"Ist es ok, nie erwachsen zu werden?" (Original)* *"Is it ok never to grow up?" (English translation)*

Post Category	Explanation	Example
Questioner	Using the Facebook Poll to obtain answers on a specific question.	*"Unter dem Reiter "Polls/Quizzes+" gibt es eine neue Umfrage zum Thema "ok.- Vanille-Glacé". Wäre cool wenn ganz viele von euch kurz mitmachen! Danke." (Original)* *"There is a new questioner under the tab "Polls/Quizzes+" on a topic "ok.- Vanilla ice-cream". It would be cool when lots of you would participate" (English translation)*
Competition	Posts related to competition, i.e. announcements, rules, winners, etc.	*"Hallo ok.- Star! Zeigt uns mit einem * vor Eurem Zitat dass Ihr auf die Bildschirme wollt."* *"Hello ok.- star! Show us with a * before your post that you want to appear on the display" (English translation)*
Advertisement	Advertisement of existing products (mostly used in a form of photo post).	*"ok.- Produkte, 5 new photos" (Original)* *"ok.- products, 5 new photos" (English translation)*
Statement	Posts in form of statement, stating opinion on certain topic.	*"Das der liebe Petrus momentan Sonne und Regen verwechselt ist nicht ok.-" (Original)* *"The fact that sun and rain are changing at the moment is not ok.-" (English translation)*

In addition, the recommendations provided by SMM practitioners were taken in consideration.

Of the above listed categories, *Product Announcements* and *Advertisement* were merged into a single category: (1) *Advertisement*. This decision was based on the fact that for the dataset used in this study, Facebook pages belong to well established brands with just a few new product launches, mostly related to a new package format.

Further, *Designed Question* and *Statement* categories were also condensed into the (2) *Engagement Booster* category since the goal of both was to increase the level of engagement. This category comprises of posts shared in form of questions, but also statements asking for direct response in form of comments and likes from the users which are considered as a good practice by the practitioners[51].

Next, the (3) *Contests* were introduced as a new category, based on suggestions by practitioners as a tool for increasing the level of engagement[52].

Finally, the posts relating to (4) *Fans Number* were separated from the *Information* category.

Apart from those, a commonly occurring content type, which was not present in the initial set, were posts discussing an external event, not necessary related to the offered product/brand. These were assigned to the (5) *Story* category.

In addition, posts referring to (6) *Facebook Applications* were assigned to a separate category, since these are also considered as a potential engagement driver[53].

Table IX summarizes the previous discussion and provides examples for each of the used content categories.

Table IX: Summary of used content categories and corresponding examples

Post Category	Abbr.	Content type(s)	Example
Advertisement	AD	Advertisements Special (price) offers Coupons	*"Spice up your breakfast with our new Cinnamon Streusel Cakes, available now in single serve!" (Original)*
Engagement Booster	EB	Asking for feedback Teasers	*"Fill in the blank: Today would be perfect if _____." (Original)*

[51] How to Boost Facebook Page Engagement. http://creativityloft.com/2012/03/how-to-boost-facebook-page-engagement/. Accessed 2012-07-12

[52] Using Facebook Contests to Boost Fan Engagement. http://addventures.com/blog/using-facebook-contests-boost-fan-engagement. Accessed 2012-07-12

[53] How to Increase Interactions And Engagement on Facebook. http://www.frogameni.com/2011/12/23/how-to-increase-interactions-and-engagement-on-facebook/. Accessed 2012-07-12

Post Category	Abbr.	Content type(s)	Example
Contest	CO	Facebook contests External contests	*"Want tickets to the Super Bowl? Turn on your webcam and grab your Doritos & Pepsi MAX for your chance to win!" (Original)*
Fans No	FN	Number of fans reached	*"Thanks to everyone for helping us get to 3million fans!" (Original)*
Story	ST	External events Non-brand related stories	*"Natascha Badmann wins her first Ironman Triathlon Championship […]"(Original)*
Facebook App	FA	References/redirection to Facebook apps	*"You're one in a million. Show us why here […] fb.drpepper.com […]" (Original)*

Posting Time

To answer the second question: *when* a post should be shared, the posting *weekday* was chosen as a factor that might influence the level of user engagement. In addition, the time for posting was also taken in consideration, thus an additional independent variable, i.e. the *hour of day* when the post was created, was added to the study.

Based on previously presented reasoning, the following independent variables were included in the study: (1) the post media type, as defined by Facebook, (2) the assigned content category, as described in previous section, (3) the weekday when posting was done, and (4) the hour of day when post was created.

7.2.2.2. Measuring the Engagement

The official measure for customer engagement over the content created by the company on a Facebook brand page, offered to the page moderators and companies through the Facebook Insights platform is the *Feedback Rate*[54], commonly referred to as *Engagement Rate*[55]. Engagement Rate is defined as a

[54] Introducing Per Post Analytics for Pages. http://www.facebook.com/note.php?note_id=263773004821. Accessed 2012-06-11

[55] How to measure the Engagement Rates of Facebook Content. http://patrickpowers.net/2011/11/how-to-measure-the-engagement-rates-of-facebook-content/. Accessed 2002-07-12

ratio between the sum of comments and likes over the post, and the number of post impressions:

$$\text{Engagement Rate} = \frac{\#\text{Likes} + \#\text{Comments}}{\#\text{Impressions}} \quad (5)$$

In formula (5), the number on impressions refers to the number of times the post was displayed on the page wall, shown in the news feed of fans or within the Fan Box widget[54]. As such, this measure is not accurate since it does not guarantee that the post was seen or read by the fan (e.g. it might have been rendered on the lower part of the page which was not visible). In addition, the engagement possibility by sharing the content, recently introduced by Facebook, is not taken in consideration in this formula.

To overcome this problem, in this study a modification of the above measure was used. The reasoning was based on the engagement possibilities described in Section 3.3: "Facebook Brand Pages", i.e. commenting, liking and sharing the content created by page moderators. Since these interaction possibilities indicate different level of engagement, separate measures were used that corresponds to each of the listed activities. Further, since the number of comments, likes and shares is not an absolute measure, but is related to the number of page fans at the moment of posting, a ratio to the number of fans was used as more accurate engagement measure. Thus, the calculation of the depended variables was performed using the following formulas:

$$LR = \frac{N_L}{N_F} \quad (6)$$

$$CR = \frac{N_C}{N_F} \quad (7)$$

$$SR = \frac{N_S}{N_F} \quad (8)$$

$$ID = D_{LI} - D_C \quad (9)$$

where N_L, N_C and N_S are the number of likes, comments and shares respectively, while N_F is the total number of fans on the day of posting. In addition, D_C, the date of creation and D_{LI}, the date of last interaction, were used to calculate the interaction duration which can be used by the company as an indicator for choosing the appropriate posting frequency.

Table X summarizes all independent and dependent variables used in the study and all of their possible values.

Table X: Summary of used variables and their possible values

Variable	Description	Values	Type	Source
MT	Media type	status, photo, video, link	Independent	Graph API
DOW	Day of week	Monday, Tuesday, …, Sunday	Independent	Graph API
HOD	Hour of day	0,..,23	Independent	Graph API
CC	Content category	(see Chapter 7.2.2)	Independent	Manual
LR	Likes ratio	Numerical	Dependent	Graph API
CR	Comments ratio	Numerical	Dependent	Graph API
SR	Shares ratio	Numerical	Dependent	Graph API
ID	Interaction duration	Numerical	Dependent	Graph API

7.2.3. Data Analysis

In order to answer the research question: which factors influence the level of customer engagement on a Facebook brand page, an analysis was performed to determine the effect that each of the selected independent variables has on each of the dependent variables. For that purpose a statistical testing was performed which revealed significant differences in the results. A Kruskal–Wallis non-parametric test for one-way analysis of variance was used, since the normality test on the data resulted in negative outcome for all of the dependent variables (CI = 95%, $p < 0.0001$). Furthermore, the post-hoc analysis was conducted through pairwise comparisons based on Mann-Whitney test with Holm's sequential Bonferroni correction (Holm 1979, pp. 65-70). Finally, the effect size, i.e. Pearson's correlation coefficient (r) was calculated using the Z value from the Mann-Whitney tests (Field 2009).

7.3. Results

Initially, descriptive statistics for the selected dependent variables were of interest. The goal was to identify the most and least commonly used form of engagement on Facebook brand pages. Figure 34 illustrates the mean values of the analyzed variables.

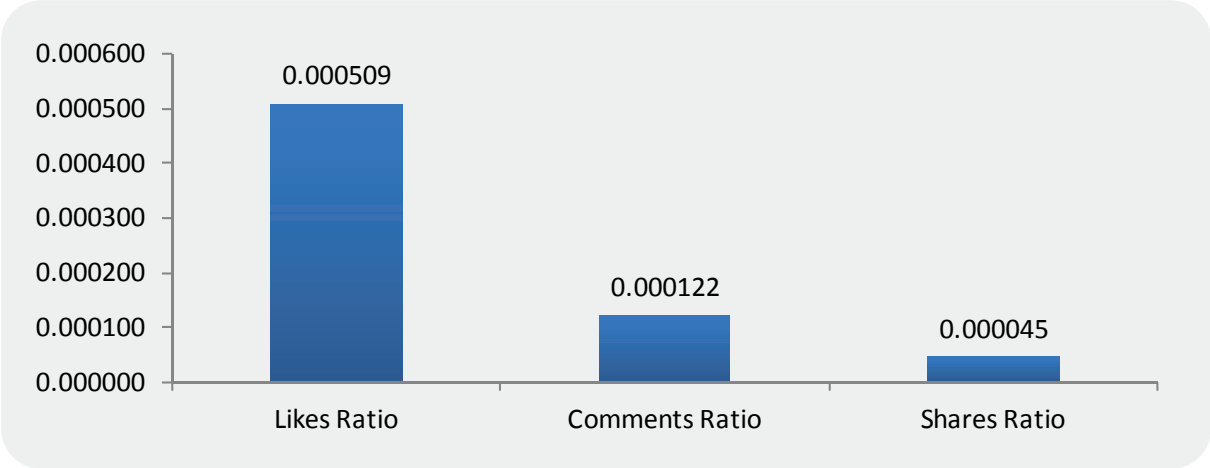

Figure 34: Mean values of engagement measures over moderator posts

Obtained results indicate that fans engage by liking the content created by the page moderators far more frequently (*M* = 0.000509, *SD* = 0.000969) compared to commenting (*M* = 0.000122, *SD* = 0.000308) and sharing (*M* = 0.000045, *SD* = 0.000601). In terms of the interaction duration, the average value was found to be 8.97 days (*SD* = 11.30).

Details of the descriptive statistics for the analyzed engagement measures are provided in Appendix II.

The continuation of this section presents the results of the analysis of the effect of the post characteristics over each of the dependent variables.

7.3.1. Post Media Type

In the selected dataset all post media types were present: *status* (1842 occurrences, 37% of total), *photo* (2032, 40%), *link* (688, 14%) and *video* (473, 9%). Table XI illustrates the descriptive statistics suitable for the selected non-parametric test: the median value (*Mdn*) and the mean rank.

Table XI: Descriptive statistics of the Kruskal Wallis test for the post media type

Media Type	LR		CR		SR		ID	
	Mdn	Mean Rank	Mdn	Mean Rank	Mdn	Mean Rank	Mdn	Mean Rank
ST	0.000242	2559.32	0.000059	3030.11	0.000000	1943.66	4.237992	2521.46
PH	0.000354	2852.76	0.000043	2557.74	0.000016	3032.41	6.046302	2729.26
LI	0.000133	1804.18	0.000016	1720.49	0.000000	2189.20	2.778194	2045.35

Media Type	LR		CR		SR		ID	
	Mdn	Mean Rank	Mdn	Mean Rank	Mdn	Mean Rank	Mdn	Mean Rank
VI	0.000158	1957.26	0.000011	1512.99	0.000012	3023.00	3.649850	2284.41

A Kruskal-Wallis test showed that there is a statistically significant difference between the engagement level over moderator posts of different post media types in terms of all engagement measures, the likes ratio ($\chi^2(3, N = 5035) = 345.550$, $p < 0.0001$), the comments ratio ($\chi^2(3, N = 5035) = 663.371$, $p < 0.0001$), the shares ratio ($\chi^2(3, N = 5035) = 675.925$, $p < 0.0001$) and the interaction duration ($\chi^2(3, N = 5035) = 127.893$, $p < 0.0001$).

The results of the post-hoc analysis obtained from the pairwise comparisons based on Mann-Whitney test showed the sources of significant difference. Details in regard to the significance level and the effect size are shown in Table XII.

Table XII: Results of the post-hoc analysis for the post media type

Media Type		LR		CR		SR		ID	
		U	r	U	r	U	r	U	R
ST	PH	1616904.5	0.12***	1531295.0	0.16***	**1064492.5**	**0.39*** **	1702809.0	0.08***
ST	LI	419623.0	0.26***	**297211.5**	**0.41*** **	582812.0	0.07**	502959.5	0.16***
ST	VI	318977.0	0.19***	**168939.5**	**0.43*** **	**235511.5**	**0.34*** **	391277.0	0.07*
PH	LI	431287.5	0.29***	471381.0	0.25***	476073.0	0.25***	519759.0	0.19***
PH	VI	322629.0	0.22***	287266.5	0.27***	-	-	399190.5	0.11***
LI	VI	-	-	147335.0	0.08**	108596.5	0.29***	147467.0	0.08**

* $p < 0.05$, ** $p < 0.005$, *** $p < 0.0001$

Significant difference was found to exist in almost all pairwise comparisons. The only two cases where there was no significant difference are in terms of liking engagement over *links* and *videos*, and sharing of *photos* and *videos*. Still, in most cases the difference in the engagement level over different media types was relatively small ($r < 0.30$). Medium effect (indicated with bold

lettering) was found to exist only for comments ratio, i.e. fans commented significantly more over *status* posts compared to the *links* and *videos*. In turn, *photos* and *videos* were shared more often compared to the *status* posts.

For easier visualization of the observed differences in the level of engagement, Figure 35 illustrates the mean ranks obtained from the Kruskal-Wallis test for the post media type grouping variable, which were used as a basis for pairwise comparisons.

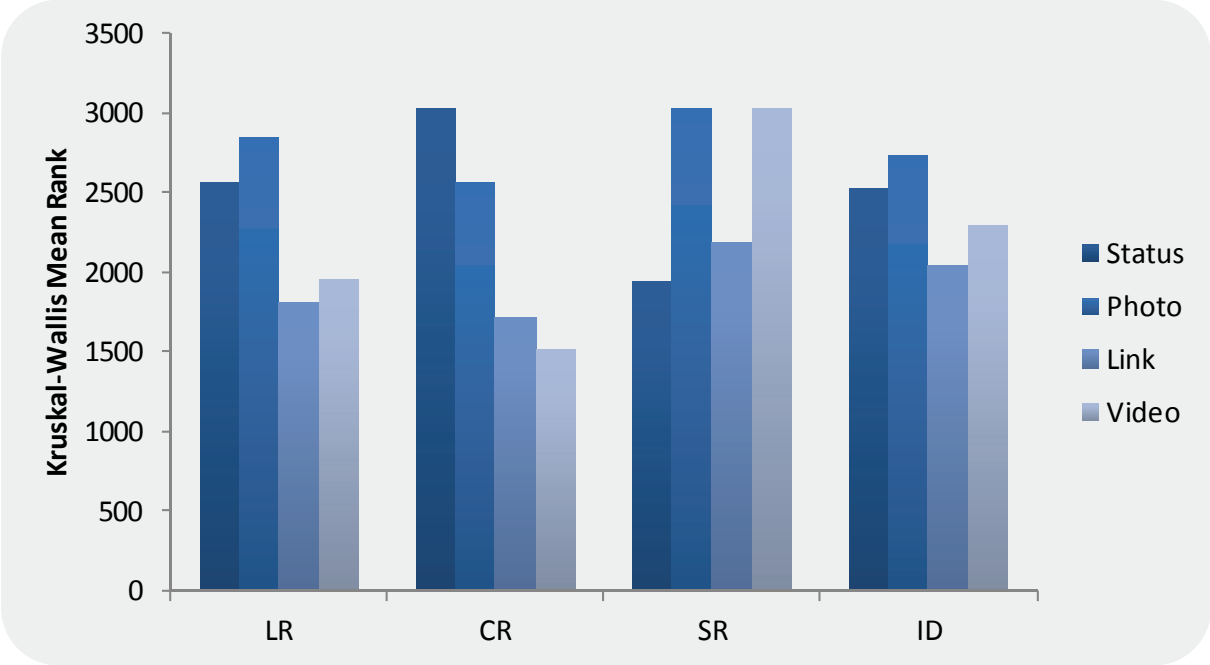

Figure 35: Mean ranks of the engagement measures using the post media type as a grouping variable

7.3.2. Content Category

Within the observed dataset, *Engagement Boosters* were the most popular content category with 2948 occurrences, thus representing 59% of the total number of posts. Of the remaining categories, *Stories* occurred within 862 posts (17%), followed by *Advertisements* (698, 14%). Less frequently used were *Contests* (387, 8%) and *Facebook App* references (110, 2%). Finally, *Fans No* appeared in less than 1% of the posts (30 occurrences).

Table XIII illustrates the descriptive statistics for each of the dependent variables.

Table XIII: Descriptive statistics of the Kruskal Wallis test for the content category

Content Category	LR		CR		SR		ID	
	Mdn	Mean Rank	Mdn	Mean Rank	Mdn	Mean Rank	Mdn	Mean Rank
AD	0.000271	2546.63	0.000035	2333.46	0.000014	2925.23	8.867350	2991.09
CO	0.000115	1657.77	0.000018	1885.58	0.000000	2100.15	4.252234	2454.62
EB	0.000302	2852.45	0.000060	3009.19	0.000003	2519.94	4.309253	2558.10
FA	0.000144	1696.95	0.000017	1770.67	0.000000	1711.84	4.391534	2424.43
FN	0.000374	3116.07	0.000032	2496.00	0.000005	2657.08	7.553536	2884.17
ST	0.000136	1821.17	0.000009	1367.63	0.000002	2467.24	2.156464	2025.45

The results of the Kruskal-Wallis test showed that there is again a statistically significant difference between the fans engagement level over moderator posts of different content categories for all engagement measures, the likes ratio ($\chi^2(5, N = 5035) = 530.122$, $p < 0.0001$), the comments ratio ($\chi^2(5, N = 5035) = 990.111$, $p < 0.0001$), the shares ratio ($\chi^2(3, N = 5035) = 129.919$, $p < 0.0001$) and the interaction duration ($\chi^2(3, N = 5035) = 178.254$, $p < 0.0001$).

To gain a better understanding of the differences between individual content categories, pairwise comparisons based on Mann-Whitney test was performed. Details in regard to the significance level and the effect size are presented in Table XIV.

Table XIV: Effect size (Pearson's correlation coefficient) obtained from the post-hoc analysis using the content category as a grouping variable

Content Category		LR		CR		SR		ID	
		U	R	U	r	U	r	U	r
AD	CO	90127.0	0.28***	107501.0	0.17***	89037.5	0.29***	105383.0	0.18***
AD	EB	910721.0	0.08***	742506.5	0.19***	867097.5	0.11***	840664.5	0.12***
AD	FA	25982.0	0.19***	28790.5	0.15***	**19603.0**	**0.30*** **	28593.5	0.15***
AD	ST	217954.5	0.24***	**180014.0**	**0.35*** **	245177.5	0.16***	199196.0	0.29***
CO	EB	290546.0	0.27***	304233.0	0.26***	477359.0	0.09***	-	-

Content Category		LR		CR		SR		ID	
		U	R	U	r	U	r	U	r
CO	FA	-	-	-	-	17657.5	0.13**	-	-
CO	FN	2068.0	0.29***	3770.0	0.16**	-	-	-	-
CO	ST	-	-	116672.0	0.24***	142186.0	0.12***	136554.0	0.15***
EB	FA	85484.0	0.15***	78843.0	0.17***	111193.5	0.10***	-	-
EB	ST	754918.0	0.29***	**469637.5**	**0.46*** **	-	-	990578.0	0.16***
FA	FN	**648.0**	**0.43*** **	1001.0	0.28**	**861.0**	**0.37*** **	-	-
FA	ST	-	-	35140.0	0.14***	32882.0	0.17***	39043.0	0.10**
FN	ST	6226.0	0.16***	5483.0	0.18***	-	-	8612.0	0.10**

** $p < 0.05$, ** $p < 0.005$, *** $p < 0.0001$*

Similar to the results obtained for the media type, in the case of content category significant difference was found to exist in almost all pairwise comparisons. Only in the case of *Fans No* there was no significant difference when compared to *Advertisements* and *Engagement Booster* for any of the engagement measures. In addition, for the liking activity, the significant difference was not found to exist between the three least liked content categories, *Story*, *Facebook App* and *Contest*.

In terms of commenting, the engagement level over the posts referring to *Contests* and those referencing *Facebook Apps* didn't show significant difference. Sharing activity showed similar level of engagement between the categories *Fans No*, *Engagement Booster* and *Story*. In addition, no significant difference was found to exist between the *Contest* and *Fans No* categories. Finally, interaction duration did not show statistically significant difference between: *Fans No*, *Engagement Booster*, *Contest* and *Facebook App*.

Although for the remaining cases a statistically significant difference was found to exist, in most of them the difference was small. Medium effect (indicated with bold lettering) occurred only between the categories *Facebook App* and *Fans No* in the case of liking and sharing activity. In addition, medium effect was found to exist between the most shared category, *Advertisement* and the least shared content category, *Facebook App*, as well as between the most and least commented categories, *Engagement Booster* and *Story*.

For easier visualization of the observed differences in the level of engagement, Figure 36 illustrates the mean ranks obtained from the Kruskal-Wallis test for the content category grouping variable, which were used as a basis for pairwise comparisons.

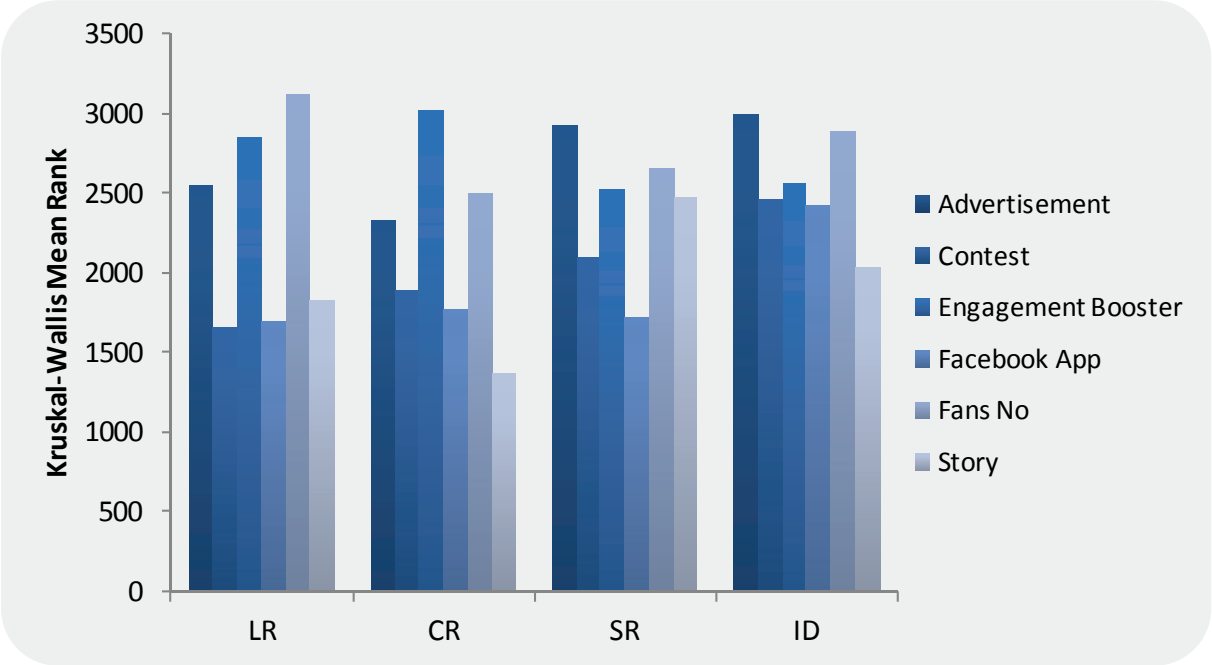

Figure 36: Mean ranks of the engagement measures using the content category as a grouping variable

7.3.3. Day of Week

From the perspective of the moderator activity there was no big difference in terms of the proportions of posts shared on different days of week: *Monday* (839 occurrences, 17% of total), *Tuesday* (826, 16%), *Wednesday* (872, 17%), *Thursday* (727, 14%), *Friday* (783, 16%), *Saturday* (436, 9%) and *Sunday* (552, 11%). Table XV illustrates the descriptive statistics.

Table XV: Descriptive statistics of the Kruskal Wallis test for the day of week grouping variable

	LR		CR		SR		ID	
Weekday	**Mdn**	**Mean Rank**	**Mdn**	**Mean Rank**	**Mdn**	**Mean Rank**	**Mdn**	**Mean Rank**
Monday	0.000246	2575.15	0.000041	2589.27	0.000005	2588.76	4.147442	2469.60
Tuesday	0.000254	2596.46	0.000042	2568.55	0.000005	2593.64	4.895046	2579.83
Wednesd.	0.000227	2424.98	0.000038	2556.74	0.000003	2510.37	4.115851	2510.79

Weekday	LR		CR		SR		ID	
	Mdn	Mean Rank	Mdn	Mean Rank	Mdn	Mean Rank	Mdn	Mean Rank
Thursday	0.000214	2395.68	0.000036	2479.03	0.000002	2494.56	5.134329	2546.55
Friday	0.000235	2510.69	0.000037	2532.46	0.000003	2496.39	5.050833	2673.42
Saturday	0.000294	2777.43	0.000035	2521.19	0.000004	2625.20	4.272656	2505.87
Sunday	0.000235	2427.22	0.000031	2301.13	0.000000	2286.17	3.305833	2261.98

Based on the variance analysis, performed through a Kruskal-Wallis test, a statistically significant effect of the weekday was found to exist over all four measures of engagement, the likes ratio ($\chi^2(6, N = 5035) = 28.483$, $p < 0.0001$), the comments ratio ($\chi^2(6, N = 5035) = 16.525$, $p = 0.011$), the shares ratio ($\chi^2(6, N = 5035) = 22.401$, $p = 0.001$) and the interaction duration ($\chi^2(6, N = 5035) = 28.832$, $p < 0.0001$).

The results of the post-hoc analysis obtained from the pairwise comparisons showed the sources of significant difference. Table XVI contains the details of the obtained results.

Table XVI: Results of the post-hoc analysis using posting weekday as a grouping variable

Weekday		LR		CR		SR		ID	
		U	*r*	*U*	*r*	*U*	*r*	*U*	*R*
Mon	Fri	-	-	-	-	-	-	301496.0	0.07**
Mon	Sun	-	-	205549.0	0.10**	203348.0	0.11***	-	-
Tue	Thu	275782.0	0.07*	-	-	-	-	-	-
Tue	Sun	-	-	203605.0	0.09**	200558.5	0.11***	199279.5	0.11***
Wed	Sat	163231.0	0.12***	-	-	-	-	-	-
Wed	Sun	-	-	215941.0	0.09**	219209.5	0.08**	216640.0	0.08**
Thu	Sat	134050.0	0.13***	-	-	-	-	-	-
Thu	Sun	-	-	-	-	-	-	178073.0	0.10**
Fri	Sat	152343.0	0.09**	-	-	-	-	-	-

Weekday		LR		CR		SR		ID	
		U	***r***	***U***	***r***	***U***	***r***	***U***	***R***
Fri	Sun	-	-	196240.0	0.08**	197791.5	0.08*	181521.0	0.14***
Sat	Sun	104906.0	0.11**	-	-	104273.5	0.12**	108174.0	0.09*

* $p < 0.05$, ** $p < 0.005$, *** $p < 0.0001$

Table XVI shows that in the case of liking, fans engage significantly more on *Saturday* compared to *Wednesday*, *Thursday*, *Friday* and *Sunday*. In addition, liking occurs in a significantly larger number on *Tuesdays* compared to the least active, *Thursday*. It can also be seen that fans write significantly less comments on content posted on *Sunday* compared to *Monday*, *Tuesday*, *Wednesday* and *Friday*. Similarly, sharing of posts created by the moderator on *Sunday* occurs less frequently compared to those posted on *Monday*, *Tuesday*, *Wednesday*, *Friday* and *Saturday*. Finally, the interaction over posts created on *Sunday* lasts shorter compared to the interaction over posts created on *Tuesday*, *Wednesday*, *Thursday*, *Friday* and *Saturday*. In addition, interaction duration of *Monday* posts lasts shorter compared to interaction duration over posts created on *Friday*.

It should be noted that although significant differences exist among the above listed pairs, in all cases the difference is relatively small. This is clearly visible from Figure 37 which illustrates the mean ranks obtained from the Kruskal-Wallis test for the weekday grouping variable.

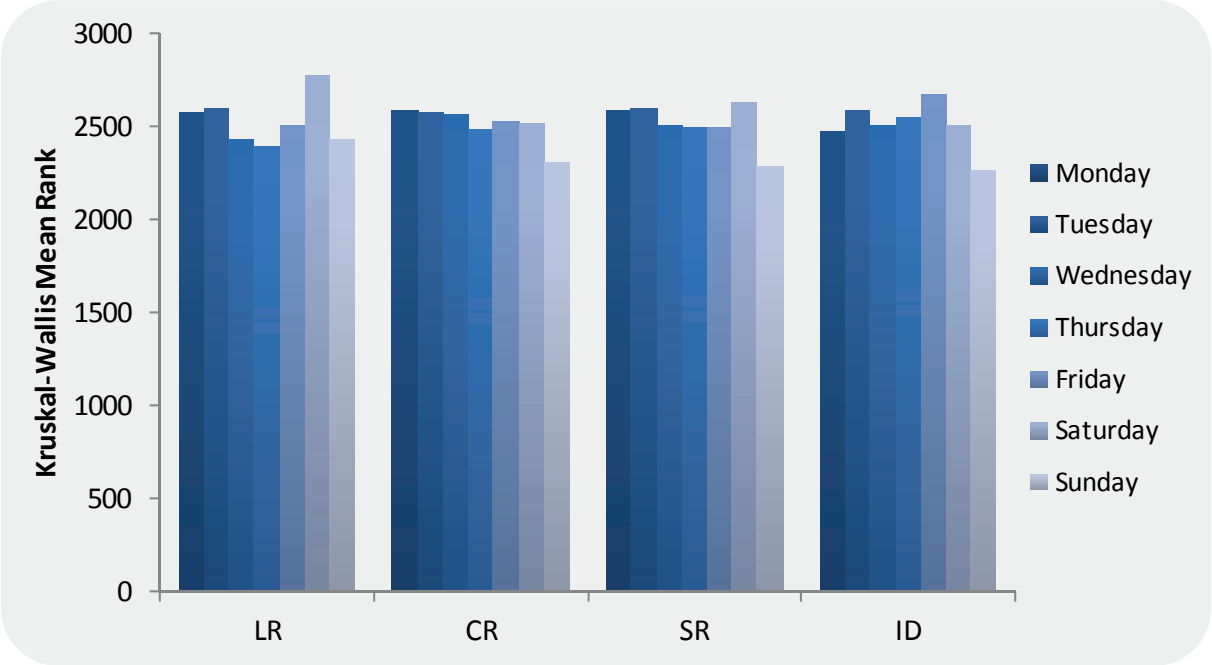

Figure 37: Mean ranks of the engagement measures using the weekday as a grouping variable

In addition to the analysis over each day of the week an additional insight was obtained by comparing the level of engagement over posts shared by the page moderator over the *weekend* (Saturday and Sunday) as opposed to those shared on *workdays*. Figure 38 illustrates the mean ranks obtained from the Mann-Whitney test, used as a basis for pairwise comparisons.

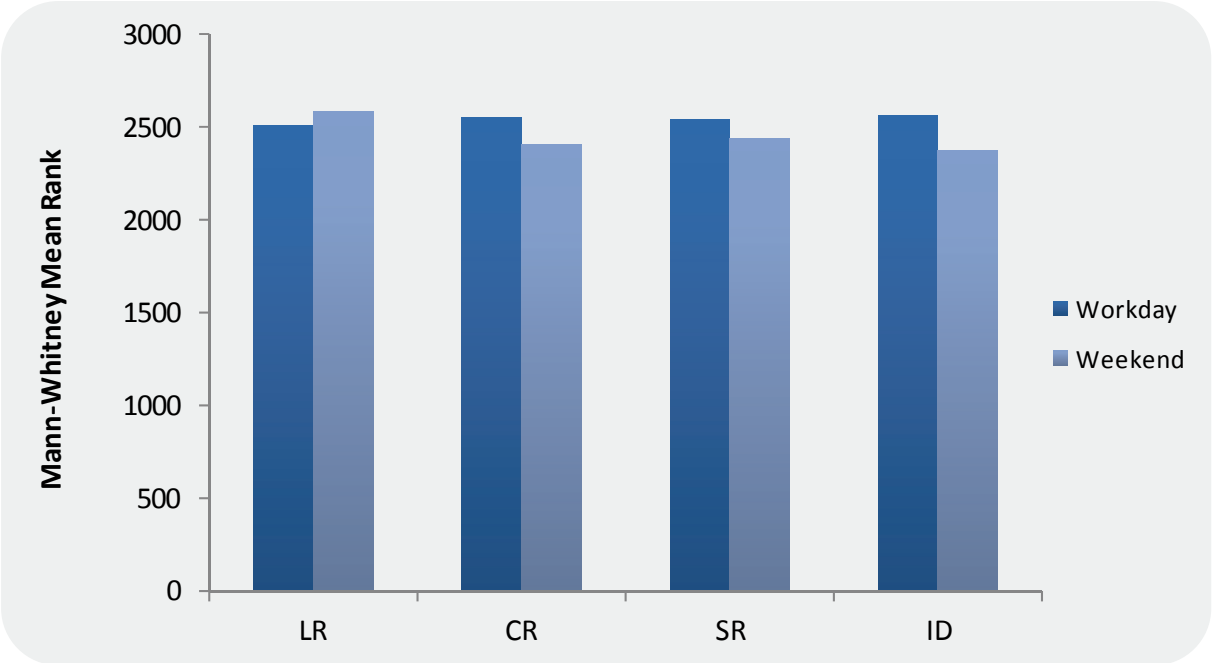

Figure 38: Mean ranks of the engagement measures using the workday/weekend as a grouping variable

A Mann-Whitney test indicated that there is a statistically significant but again small difference between the number of comments written over the posts shared on *workdays* (*Mdn* = 0.000038, mean rank = 2547.24) compared to those shared over the *weekend* (*Mdn* = 0.000034, mean rank = 2398.24), U = 1880897.5, p = 0.004, r = 0.04, i.e. fans comment more during the *workdays*.

Similar results were obtained for the sharing action - sharing of content posted by the moderators on *workdays* (*Mdn* = 0.000004, mean rank = 2538.07) compared to content posted over the *weekend* (*Mdn* = 0.000002, mean rank = 2435.78) was significantly larger, but again with a very small difference, U = 1917988.0, p = 0.041, r = 0.03.

Finally, interaction over posts created on *workdays* (*Mdn* = 4.556944, mean rank = 2554.23) lasted longer compared to the interaction over posts created on *weekend* (*Mdn* = 3.904189, mean rank = 2369.61), U = 1852604.0, p < 0.0001, r = 0.05.

In the case of liking there was no significant difference (p = 0.124).

7.3.4. Time of Day

In the observed dataset, moderators showed the highest level of activity in the period between 2pm and 2am (4216 posts, 84% of total). Table XVII contains the descriptive statistics providing the number of posts shared by the moderators for each hour of day, as well as the median values and the mean ranks for each of the dependent variables.

Table XVII: Descriptive statistics of the Kruskal Wallis test for hour of day grouping variable

		LR		CR		SR		ID	
H	N	Mdn	Mean Rank	Mdn	Mean Rank	Mdn	Mean Rank	Mdn	Mean Rank
0	168	0.000200	2290.39	0.000025	2203.45	0.000001	2249.51	3.420590	2193.64
1	178	0.000184	2294.29	0.000025	2254.73	0.000001	2299.21	4.093808	2338.54
2	102	0.000162	2162.40	0.000037	2426.80	0.000000	1946.16	2.983814	2242.79
3	69	0.000237	2515.86	0.000036	2448.06	0.000002	2444.08	4.842106	2655.26
4	43	0.000556	3257.53	0.000044	2790.07	0.000009	3023.49	3.578877	2215.80
5	58	0.000501	3317.20	0.000057	2829.28	0.000015	3194.08	2.019606	1931.78

H	N	LR		CR		SR		ID	
		Mdn	Mean Rank	Mdn	Mean Rank	Mdn	Mean Rank	Mdn	Mean Rank
6	80	0.000643	3719.86	0.000049	2738.24	0.000014	3119.15	3.974653	2430.67
7	40	0.000881	3839.75	0.000086	3128.18	0.000016	3178.39	2.755602	2230.33
8	56	0.000503	3510.21	0.000055	2970.98	0.000008	2742.56	3.945203	2369.07
9	77	0.000421	3249.38	0.000109	3447.68	0.000022	3123.01	2.916458	2201.25
10	58	0.000428	3166.81	0.000079	3194.50	0.000009	2826.91	3.164664	2455.09
11	48	0.000441	3227.85	0.000060	2744.27	0.000013	2997.35	3.592558	2250.91
12	66	0.000297	2713.21	0.000039	2415.64	0.000010	2865.45	3.479381	2370.17
13	122	0.000352	3035.21	0.000038	2567.23	0.000019	3222.00	7.430909	2896.39
14	224	0.000367	2999.43	0.000057	3026.03	0.000007	2698.91	3.075330	2443.26
15	353	0.000269	2647.03	0.000040	2571.39	0.000016	2995.42	4.143692	2457.80
16	466	0.000277	2694.75	0.000054	2890.12	0.000003	2482.61	5.387008	2719.68
17	516	0.000232	2498.89	0.000037	2538.57	0.000006	2613.35	4.790868	2567.77
18	385	0.000179	2254.45	0.000030	2359.93	0.000001	2281.27	4.138808	2414.41
19	375	0.000167	2082.57	0.000026	2244.29	0.000000	2187.02	4.078241	2440.96
20	367	0.000192	2126.30	0.000025	2144.79	0.000001	2301.11	5.123935	2613.91
21	550	0.000236	2443.40	0.000039	2539.62	0.000002	2357.49	6.261007	2752.39
22	376	0.000200	2284.04	0.000031	2373.80	0.000002	2434.50	4.254682	2501.61
23	258	0.000194	2282.92	0.000028	2215.24	0.000001	2424.53	4.956348	2566.30

The results of the statistical analysis showed that the hour of the day when the post was created is also an important factor that makes statistically significant difference for all four measures of engagement, the likes ratio ($\chi^2(23, N = 5035) = 341.303$, $p < 0.0001$), the comments ratio ($\chi^2(23, N = 5035) = 193.989$, $p < 0.0001$), the shares ratio ($\chi^2(23, N = 5035) = 225.043$, $p < 0.0001$) and the interaction duration ($\chi^2(23, N = 5035) = 73.436$, $p < 0.0001$).

The results of the post-hoc analysis obtained from the pairwise comparison based on Mann-Whitney test showed the sources of significant difference

which occurred among 155 pairs, out of 253 possible combinations. In summary, posting hour showed the greatest effect over the liking activity, i.e. 121 significant differences were found to exist. Of those, 37 pairs showed medium sized effect. The lowest effect was observed in the case of interaction duration with only 20 cases of statistically significant differences, only 1 of them being medium sized. To maintain the readability, the complete table containing details of the post-hoc analysis is provided in Appendix III.

Since the above discussed results introduce challenges for interpretation due to the large number of cases, to simplify the analysis and draw meaningful conclusion that could be used by the practitioners an additional analysis was performed by defining two periods of time when the content was created by the page moderators, i.e. *low hours* (between 2am and 2 pm) and *peak hours* (from 2pm until 2am).

Visualization of the number of posts shared over different hours of the day, illustrated on Figure 39 clearly explains the reasoning behind the intervals selection. It can be seen that during the peak hours moderators posted 84% of the all the posts from the observed dataset. Similar posting pattern was already recognized from a study conducted by the consultancy company Momentus Media (2011).

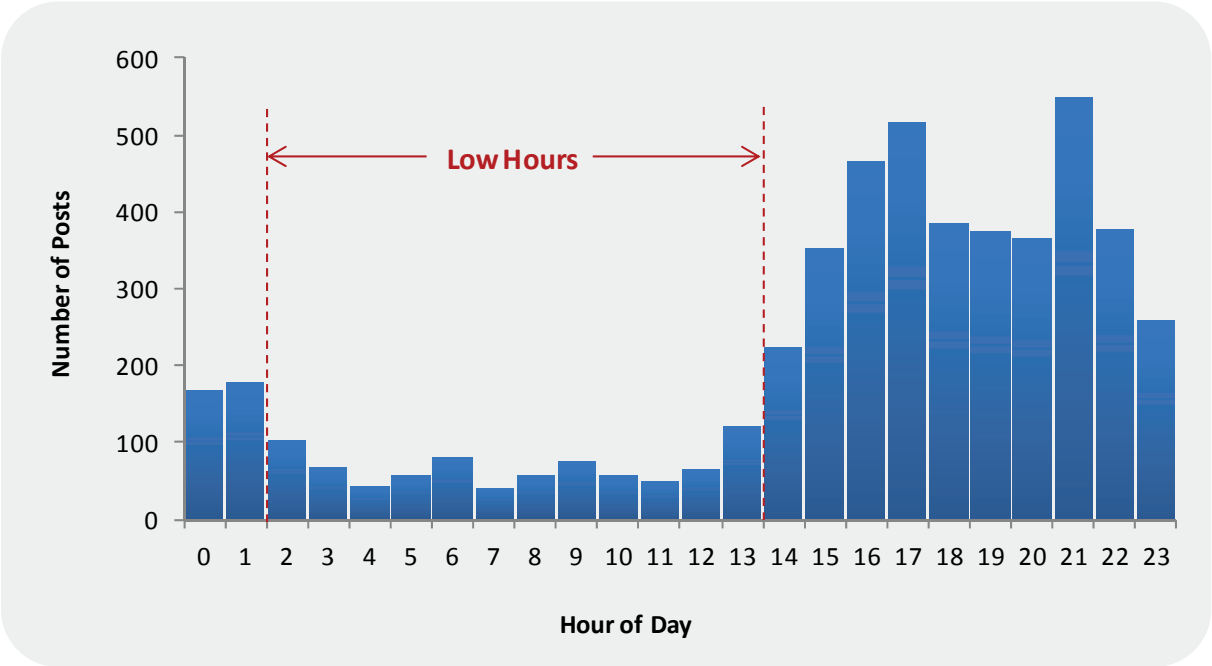

Figure 39: Distribution of moderators' posts over the day

A Mann-Whitney test of variance indicated that there is a significant difference in the engagement level of the fans over the posts created by page moderators during the *high hours* compared to the engagement over posts created during

the *low hours*. Fans liked the content shared during the *low hours* (*Mdn* = 0.000380, mean rank = 3067.84) more compared to the content shared during the *peak hours* (*Mdn* = 0.000380, mean rank = 3067.84), $U = 1276129.5$, $p < 0.0001$, $r = 0.17$.

Similarly, content created during the *low hours* (*Mdn* = 0.000052, mean rank = 2767.02) received more comments compared to the content shared during the *peak hours* (*Mdn* = 0.000035, mean rank = 2469.62), $U = 1522501.5$, $p < 0.0001$, $r = 0.08$.

Finally, sharing of content posted during the *low hours* (*Mdn* = 0.000009, mean rank = 2861.02) occurred more frequently compared to the content posted during the *peak hours* (*Mdn* = 0.000003, mean rank = 2451.36), $U = 1445518.5$, $p < 0.0001$, $r = 0.11$.

Only in the case of interaction duration, the results were the opposite, i.e. fans interacted longer over the content posted during the *peak hours* (*Mdn* = 4.626186, mean rank = 2540.98) compared to the content posted during the *low hours* (*Mdn* = 3.584028, mean rank = 2399.71), $U = 1629570.0$, $p = 0.011$, $r = 0.04$.

For easier visualization, Figure 40 illustrates the mean ranks obtained from the Mann-Whitney test used as a basis for pairwise comparison.

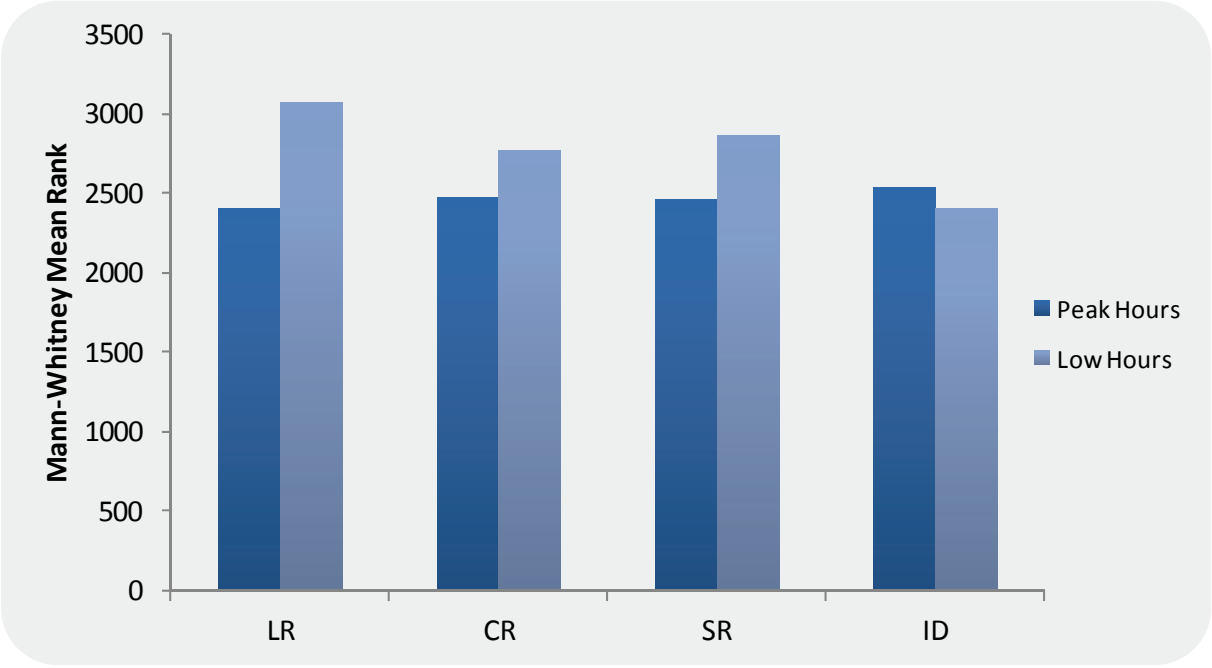

Figure 40: Mean ranks of the engagement measures using the peak/low hours as a grouping variable

When looking at the posting activity of the fans, the obtained results are similar to those for page moderators, i.e. fans post least during the morning and early afternoon. This result complies with the previous findings from studies over temporal messaging patterns on Facebook (Golder et al. 2007, pp. 41-66).

Illustration for the number of posts shared by fans during the day is provided on Figure 41.

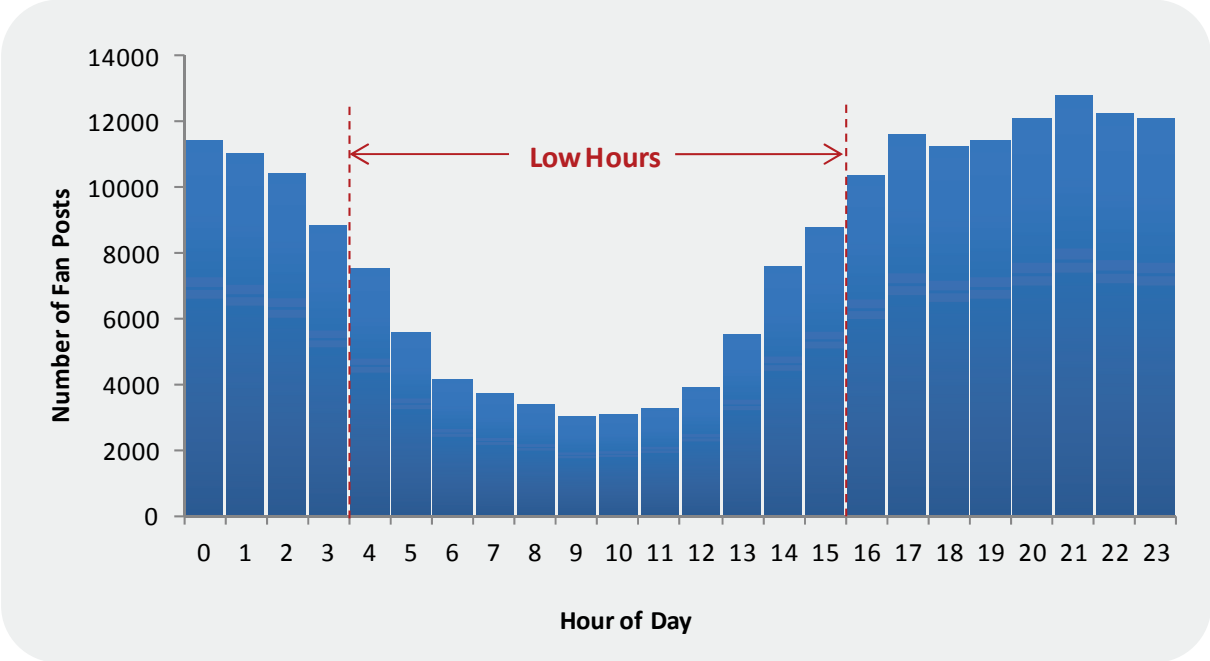

Figure 41: Distribution of fans' posts over the day

A further study could address the temporal patterns of liking and commenting by analyzing their timestamps. This would provide more insights into the interaction duration in terms of explaining the percentage of comments and likes over time.

7.4. Discussion and Managerial Implications

The results presented in the previous section confirmed that different characteristics of the content shared by the page moderators have effect on the engagement level of the fans on a Facebook brand page. Thus the main implication to be drawn from this study for the SMM practitioners would be:

> *I1: Social media marketing practitioners should prepare clear posting strategies to increase the level of engagement over the moderator posts.*

7.4.1. Media Type

Post media type was found to have an effect on all four measures for user engagement. Thus the following recommendation can be given:

> *I2: Post media type represents an important factor to be included in the posting strategies of the Facebook brand page moderators since it influences the number of likes, comments, shares and interaction duration.*

On overall level, calculated as a sum of mean ranks of all engagement measures, *photos* caused the greatest level of engagement, followed by *status* posts, *videos* and *links*. This result complies with the one obtained from the previously conducted case study (Pletikosa and Michahelles 2011b, pp. 161-170), but also with the results obtained in two similar studies conducted by social media consulting agencies (Momentus Media 2011; Virtue 2011). The explanation for this behavior can be found in the existing research from the field of Human-Computer Interaction (HCI). The results obtained through an eye-tracking study on Facebook brand pages indicated that *photos* attract a lot of attention and represent the first fixation area on the screen[56].

When compared to other multi-media content, i.e. *videos* and *links,* an explanation for the lower level of interaction might found in the fact that these two media types are more time consuming. In addition, they cause a redirection to another web page thus increasing the possibility that no further engagement will occur on the Facebook brand page.

Looking at the individual engagement measures, the likes ratio and interaction duration have the same order of media type preference as on the overall level. In the case of sharing there is a slight difference, while *photo*, *video* and *link* posts maintain their order, *status* posts display the lowest level of sharing. A possible explanation might be that fans find multi-media content as more appealing than pure text and as such they would like to share it with their friends. In addition, since majority of status posts from the observed dataset belong to the *Engagement Booster* content category (86%), sharing these posts outside the Facebook brand page would be out of context. In turn, the same reasoning can be applied to explain the greatest number of comments over the *status* posts.

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[56] Here's What People Look at on Facebook Brand Pages. http://mashable.com/2011/12/14/eyetracking-facebook-brand-pages/. Accessed 2012-07-13

The previous discussion can be summarized in the form of the following managerial implication:

> *I3: Facebook brand page moderators should post photos since these represent a media type that triggers the largest level of engagement while links result in the least engagement from the fans.*

7.4.2. Content Category

In the case of content category there was also a significant effect over all four measures for user engagement. Thus the following implication can be drawn:

> *I4: Content category represents an important factor to be included in the posting strategies of the Facebook brand page moderators since it influences the number of likes, comments, shares and interaction duration.*

An interesting finding from the post-hoc analysis was that despite the fact that the posts referring to *Fans Number* occurred in less than 1% of the posts, they caused the greatest volume of interaction on overall level with highest value of likes ratio and a second most popular category for the remaining three engagement measures. Looking at the findings from previous studies focusing on the consequences of brand community participation, such as commitment, emotional attachment and loyalty (Andersen 2005; Casalo et al. 2007; Chan and Li 2010; Ulusu 2010), it is of no surprise that fans share the excitement for the mutually achieved success.

Of the remaining categories, *Engagement Boosters* and *Advertisements* resulted in high level of engagement, while the *Story*, *Facebook App* and *Contest* were the three least popular content categories. Since the *Engagement Boosters* are designed in form of questions and/or teasers, asking from a direct feedback from the fans, this result is of no surprise. In addition, similar finding was already reported in terms of achieving higher level of interaction with posts that explicitly ask users to like them or comment over them (Momentus Media 2011).

Similarly, no surprise comes for the *Advertisement* category which occurred at the top position in the previous study and can also be supported by findings from previous research on brand communities showing that users are interested in receiving brand announcements on their pages (Li 2007a; Ulusu 2010, pp. 2949-2957).

At the individual level, the likes ratio has the same order of content category preference as on the overall level. For the remaining three engagement measures, the same three leading categories were present with a slight difference in the order, i.e. the *Engagement Booster* category attracted the largest number of comments, followed by *Fans No* and *Advertisement*, while the *Advertisements* were shared the most and have caused the longest interaction duration.

Similarly, for the last three categories, slight differences in the order were observed. *Stories* were shared more frequently that *Contest* and *Facebook App* posts, with lowest number of comments and over the shortest period of time. The order of *Contest* and *Facebook App* posts remained unchanged indicating greater interest in winning a tangible prize than participating in a Facebook App providing only virtual reward.

To summarize the above discussion we derive the following implication:

> *I5: Facebook brand page moderators should create posts which refer to Fans No, Engagement Boosters and Advertisements since these are the most popular content categories resulting in highest level of engagement from the fans.*

7.4.3. Weekday

The posting day was also found to be a significant factor for fan engagement. Thus the following implication can be stated:

> *I6: Weekday represents an important factor to be included in the posting strategies of the Facebook brand page moderators since it influences the number of likes, comments, shares and interaction duration.*

On overall level, the engagement over posts created on *Saturday* was highest, followed by *Tuesday*, *Monday*, *Friday*, *Wednesday* and *Thursday*. Surprisingly, the engagement over posts created on *Sunday* was lowest.

On individual level, each of the engagement variables displayed different behavior. For the likes and shares ratios, the best days for posting were found to be *Saturday*, *Tuesday* and *Monday*. *Monday* and *Tuesday* were among top three posting days for increasing the comments ratio, followed by *Wednesday*. In case of interaction duration, posts shared by page moderators on *Friday* showed highest level of engagement, followed by *Tuesday* and *Thursday*.

The commonality between the obtained results for all engagement measures is that *Tuesday* appears on the second position for all engagement measures, while *Sunday* is at the last position for comments and shares ratio, and interaction duration, while for the likes ratio it is not on the last position, but the difference to the last weekday, i.e. *Thursday* is very small.

Obtained results are similar to those reported in the Virtue study (2011): engagement level followed the same temporal distribution: a U-shaped distribution occurred over the workdays, followed by decrease during the weekend.

The results of the aggregated analysis, i.e. posting over the *weekend* vs. *weekdays*, showed that the number of comments, likes and shares was higher over posts shared on *weekdays*, compared to the posts shared on *weekend*. This finding again complies with the one obtained from Virtue (2011). Still, no significant difference was found to exist over the likes ratio. The results for interaction duration were the opposite, i.e. interaction duration over posts created during the *weekend* was higher compared to those shared on *weekdays*. An explanation for the above presented results can be found in the general temporal rhythmus of interactions on Facebook (Golder et al. 2007, pp. 41-66) indicating that Facebook users interact more on *workdays*. Thus:

> *I7: Facebook brand page moderators should post during the workdays to trigger highest level of fan engagement.*

7.4.4. Time of Day

The final factor analyzed in this study was the time of day. The obtained results showed that this factor also has significant effect over all four measures of engagement. Thus the following implication can be stated:

> *I8: Posting time represents an important factor to be included in the posting strategies of the Facebook brand page moderators since it influences the number of likes, comments, shares and interaction duration.*

Without entering into the details of each individual difference between separate hours a generalization can be made by pointing out that on overall level, user engagement was highest over the content shared during the morning and early afternoon. This period corresponds to the *low hours* for posting activity undertaken by the page moderators. Pairwise comparisons

showed that the greatest level of variance exists in the case of liking engagement, while the lowest effect was seen over the interaction duration.

This was also confirmed by looking at the results of the aggregated analysis. The time of day, divided into *low* and *peak hours*, was found to be an important factor over the engagement level of the fans over the posts created by page moderators. Differences between the engagement level over the content created during the *high hours* when compared to posts created during the *low hours* were found to exist for the likes ratio, comments ratio and shares ratio. In all three cases the engagement level was higher during the *low hours*. Only in the case of interaction duration, the results were the opposite, i.e. fans interacted longer over the content posted during the *peak hours*.

These results comply with those obtained from the similar studies (Momentus Media 2011; Virtue 2011). Both sources recommended posting during the *low hours* to boost the engagement. An assumption can be made that this behavior is related to the "habit" of Facebook fans to "check the news" before going/starting to work or study. Therefore, the final proposed implication is:

> *I9: Facebook brand page moderators should create content during the morning and early afternoon in order to trigger the higher level of engagement from the fans.*

7.5. Summary, Limitations and Future Work

This study presented in this chapter evaluated the effect of the characteristics of the content shared by a company on Facebook brand pages over the level of user engagement. Two basic questions that correlate to the categorization of the content created by the page moderator were addressed: (1) which *content* should a moderator post on the wall and (2) *when* the content should be posted. In addition, a measure for the level of engagement over individual posts was proposed based on the number of undertaken actions over the content created by page moderators, i.e. number of comments, likes and shares, in relation to the number of fans, as well as the interaction duration.

The results showed that there is a significant effect of all of the analyzed factors over all of the selected engagement measures. In addition, a detailed analysis was provided for each engagement factor in order to derive implications for SMM practitioners. These findings should encourage moderators of Facebook brand pages to prepare clear posting strategies that trigger the activity of users and drive adoption in the long run.

The results presented in this study are limited to *Food/beverages* Facebook brand page category. In order to confirm these findings and identify specific industry domains that display different behavior, the proposed analysis should be expanded to other categories of Facebook brand pages. In addition, additional factors that might influence the level of engagement, such as posting frequency, post length, etc., should be investigated. Finally, comparison to the engagement over the posts shared by the fans would provide insights into the level of influence of the individual users, i.e. “superfans” (Harris and Rae 2009, pp. 24-31) compared to the brand page moderator.

Summary of Main Findings

- Level of engagement on Facebook brand page over the content created by the company can be measured through the number of undertaken actions, i.e. likes, comments and shares, and interaction duration.
- Level of engagement over posts created by the moderator on Facebook brand pages can be increased by choosing the appropriate (1) media type, (2) content type, (3) posting day and (4) time.
- *Media type*: Photos are the media type that triggers the largest level of engagement while links result in the least engagement from the fans; in addition, while status posts result in higher volume of comments, multimedia types (photos, videos, links) are those that are being shared.
- *Content category*: Posts referring to Fans No, Engagement Boosters and Advertisements are the most popular content categories.
- *Posting day*: On Facebook brand pages users engage in higher volume over posts created on weekdays compared to those created on weekends; Posts created on Sunday exhibit the lowest engagement rates, but also the middle of the week shows low level of user activity.
- *Posting time*: While moderators post mostly in the peak hours, the user behavior is the opposite - posts created during the low hours, i.e. in the morning and early afternoon, cause the largest level of user engagement.

8. Increasing Engagement, Loyalty, Word-of-Mouth and Growth on Facebook Brand Pages

Determining the value of social media is one of the most important questions for the companies considering whether to include SMM into their marketing initiatives. Still, objectives of SMM differ from those of traditional media, thus making the measurement of effectiveness difficult. This problem is partially due to the fact that most of the existing frameworks for evaluation are still driven by the "reach and frequency" approach. As such these frameworks are not suitable for interactive social media platforms (Hoffman and Fodor 2010, pp. 41-49).

The study presented in this chapter addresses the research question RQ9: "What is the relation between the engagement, loyalty, word-of-mouth and growth on SMM platforms?" presented in Chapter 1.2.1.3: "Engagement on Social Media Platforms". It represents a continuation of the study presented in Chapter 7: "Customer Engagement on Facebook Brand Pages". It extends the presented findings by integrating them with the existing marketing theories to find more accurate explanation for the observed effects. Further, based on the review of previous work in the field of online advertising and community participation, additional potential factors are identified and based on that a model for prediction is proposed which reveals the relations between the content design and characteristics, scheduling, page focus and communication policy as factors that influence the level of engagement as one of the main SMM objectives. Furthermore, the proposed model explains the relations between the engagement, and traditional marketing constructs, i.e. loyalty, word-of-mouth communication and community growth on Facebook brand pages.

This study was submitted for publication in the "Wirtschaftsinformatik" journal under the title "Increasing brand engagement, loyalty and growth among

consumers on Facebook brand pages: An empirically supported model" (Pletikosa Cvijikj et al. 2013b). Thus this section contains excerpts from the referenced publication which are not further demarcated in the text.

8.1. Introduction

With the growing number of companies integrating social media into their marketing communications, the return-on-investment (ROI) of social media marketing became of interest. While traditional marketing approach for ROI estimation is based on cost and revenue calculations, faced with the complexity of applying such method to social media, practitioners began embracing a return-on-interaction interpretation instead[57]. This new interpretation shifted the focus from financial to non-transactional customer behavior (Brodie et al. 2011, pp. 252-271), which in turn provides opportunity to develop SMM strategies that fit with existing marketing objectives, such as brand engagement, WOM communication and brand awareness (Hoffman and Fodor 2010, pp. 41-49).

To contribute in this direction, this study provides a coherent model which explains (1) the relation between individual content characteristics as factors that influence the level of brand engagement, and (2) the relation between engagement and (a) loyalty, (b) WOM communication, (c) growth and (d) community size. The proposed model is empirically evaluated, based on the large dataset consisted of all activities over two months on the top 100 Facebook brand pages in the Food/Beverages category.

The continuation of this chapter is structured as follows. Section 2 constructs the conceptual framework and derives the hypotheses. Section 3 describes the used methodology. The results of the analysis are presented in Section 4, while Section 5 discusses the findings and proposes implications for SMM practitioners. Finally, Section 6 provides a summary, discussion on the limitations of this study and proposes ideas for future work.

8.2. Theoretical Framework

Theoretical framework proposed in this study is illustrated on Figure 42.

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[57] ROI = Return on investment? Nope. http://www.toddpillars.com/roi-return-on-interaction/. Accessed 2012-06-14

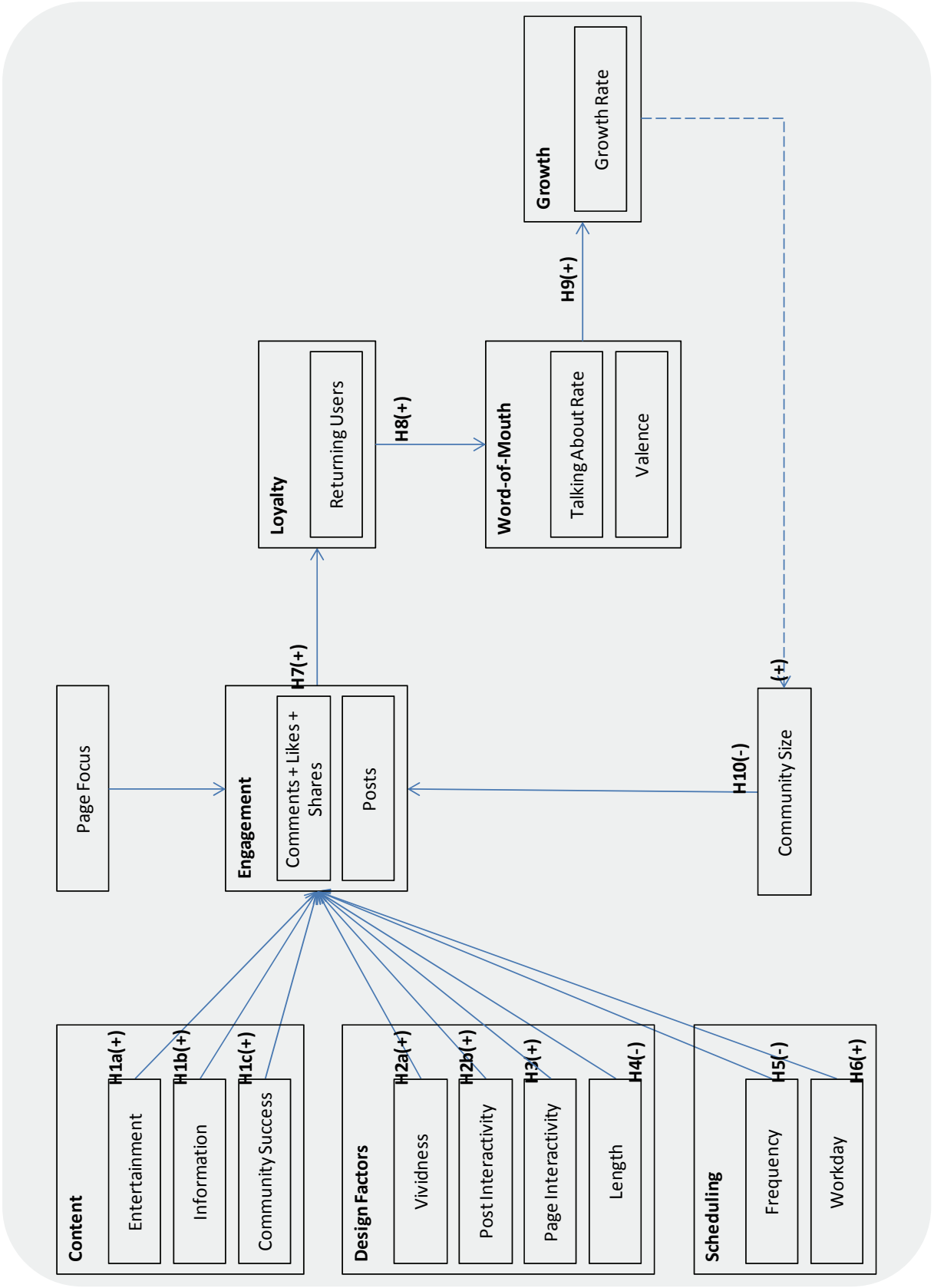

Figure 42: Theoretical framework showing the relationship of brand page activity to brand engagement, loyalty, word-of-mouth and growth

The proposed framework is based on the hypotheses derived from theories and knowledge from the following research fields: in order to understand the motivations for participation, the classical concepts of Uses and Gratifications (U&G) theory were employed (Katz 1959, pp. 1-6), providing the possibility to understand the responses to different dimensions of gratification which lead towards brand engagement (Brodie et al. 2011, pp. 252-271). Further, following the example of De Vries et al. (2012, p. 83-91), an analogy to the online advertisement was made in order to determine which design factors could increase the level of engagement. In addition, brand community participation was added as a factor that might influence brand loyalty and brand awareness (Casalo et al. 2007, pp.775-792; Godes and Mayzlin, 2004; pp. 545-560). Finally, brand engagement was also reviewed from the sociological perspective by adding the community size as an important factor.

Thus, the proposed framework supports the following idea: if the content posted by page moderators on a Facebook brand page satisfies particular user needs and is designed well, this would lead to higher level of user engagement, which in turn, would result into higher level of brand loyalty, thus also indirectly increasing brand awareness.

The continuation of this section provides the details of the underlying reasoning and formulates the hypotheses.

8.2.1. Content

U&G theory is an approach frequently applied by technology and media researchers to understand the goals and motivations of individuals for engagement with different forms of media. As such, it was recently applied to social media to identify and explain different interaction patterns and behaviors (Chung and Austria 2010, pp. 581-586; Smock et al. 2011, pp. 2322-2329).

Previous studies of online platforms distinguish between three main gratification areas: content, relationship-oriented and self-oriented areas (Jahn and Kunz 2012, pp. 344-361). Of these, this study is focused on the content area, as a determinant which is being controlled by the page moderator. Further, a distinction is made between hedonic and functional dimensions of the content which might influence the affective and cognitive responses (Kempf 1999, pp. 35-50). The hedonic dimension, i.e. providing entertaining content, was already found to be an important factor on online platforms which increases the engagement level (Dholakia et al. 2004, pp. 241-263; Park

et al. 2009, pp. 729-733). Translated to the domain of a Facebook brand page, the similar behavior could be expected. Thus the following hypothesis was formulated:

> *H1a: Level of engagement on Facebook brand pages can be increased by providing entertaining content to the fans.*

In terms of functional gratification, the importance of delivering information through advertisements was already recognized for traditional media (Rubin 2002, pp. 525-548). In addition, receiving information about the brand was found to be one of the main reasons for participation in online brand communities (Muntinga et al. 2011, pp. 13-46; Raacke and Bonds-Raacke 2008, pp. 169-174; Ulusu 2010, pp. 2949-2957). Based on these previous findings, it could be expected that informative content would be perceived as valuable of Facebook brand pages, which should lead towards the increased level of engagement. Thus the following hypothesis can be made:

> *H1b: Level of engagement on Facebook brand pages can be increased by providing informative content to the fans.*

Finally, looking at the findings from studies focusing on the consequences of brand community participation, such as commitment, emotional attachment and loyalty (Andersen 2005, pp. 39-51; Casalo et al. 2007, pp. 775-792; Chan and Li 2010, pp. 1033-1040; Ulusu 2010, pp. 2949-2957), an assumption can be made that fans would share the excitement for the achieved community success, thus stating:

> *H1c: Level of engagement on Facebook brand pages can be increased by making references to the community success.*

8.2.2. Design Factors

8.2.2.1. Vividness and Interactivity

Vividness has been considered an important persuasion tool in the psychology research (Taylor and Thompson 1982, pp. 155-181). Within the online platforms it has been referred to as media richness (Daft and Lengel 1986, pp. 554-571). However, when it comes to interactivity, there are different interpretations. While communication researchers relate interactivity to the communication policy, which can vary within the same medium (Rafaeli 1990, pp. 125-181), from technology perspective it refers to the degree to which users can influence the form and content of the media environment (Steuer 1992, pp.73-93).

Previous studies found existence of positive correlation between vividness and effectiveness of online advertisement, measured by the level of interaction with the online ad, i.e. the click-through rate (CTR) (Lohtia et al. 2003, pp. 410-418; Fortin and Dholakia 2005, pp. 387-396). Thus fans are likely to react positively to moderator posts containing high levels of vividness, resulting in increased level of engagement. Therefore, the following prediction can be made:

> *H2a: The higher the level of post vividness, the higher the engagement level is.*

In case of interactivity as a factor, there are no clear conclusions, mostly due to the inconsistencies between the definitions and operationalizations of the construct (Liu and Shrum 2002, pp. 53-64). While some authors report the existence of a positive effect (Cho 1999, pp. 201-215), others recommend usage of "the optimal mix", i.e. high level of vividness and a moderate level of interactivity (Fortin and Dholakia 2005, pp. 387-396). Based on these findings similar effect could be expected on Facebook brand pages, i.e. posts containing higher level of interactivity would result in higher level of engagement, thus:

> *H2b: The higher the level of post interactivity, the higher the engagement level is.*

Apart from the post interactivity, a page's interactivity which corresponds to the communication policy of the Facebook brand page should be taken in consideration (Rafaeli 1990, pp. 125-81). Since lower page interactivity prevents fans from posting, an assumption can be made that fans will not fell connected to these pages, resulting in lower level of engagement. Thus the following hypothesis is proposed:

> *H3: The higher the level of page interactivity, the higher the engagement level is.*

8.2.2.2. Post length

An additional element to be considered as a design related factor is the message length. In the domain on online advertising it was shown that banners with lengthy messages receive fewer clicks (Baltas 2003, pp. 505-513). Similar results were obtained for the Facebook brand pages, i.e. a very small negative effect was found to exist, but only for the number of likes (De Vries et al. 2012, pp. 83-91). Based on these finding a similar outcome could be expected on Facebook brand pages thus the following hypothesis can be added:

H4: Length of a post has a negative effect on the level of engagement on Facebook brand pages.

8.2.3. Scheduling

The concept of scheduling was already recognized as an important element of marketing strategies which could potentially lead to increased revenue (Adler et al. 2002, pp. 103-119; Kumar et al. 2006, pp. 1067-1189). Frequency of ad exposure, as one dimension of scheduling, attracted the attention of scholars for both traditional and online media. Still, findings of previous studies remain inconclusive - while some authors report positive effect (Pechman and Stewart 1992, pp. 285-330; Dreze and Hussherr 2003, pp. 8-23), others report the opposite (Chatterjee et al. 2003, pp. 520-541; Kirmani 1997, pp. 77-86). This conflict mostly originates from the usage of different metrics for effectiveness: CTR versus recall. In general scholars agree that high frequency increases recall, but reduces the CTR (Robinson et al. 2007, pp. 527-541). Making an analogy between CTR and engagement over posts shared by the moderator on a Facebook brand page, the following could be expected:

H5: Higher posting frequencies result in a lower level of engagement.

Web based advertising usually assumes having a time and space slot on an online platform of predefined size and duration where the advertisement will be shown (Kumar et al. 2006, p. 1067-1089). In the case of Facebook brand pages, the situation is different. When the moderator posts content on the wall, it will appear on the top of the brand page and on the page fans' walls. Still, people's Facebook walls are overloaded with content coming from multiple sources (e.g. posts from friends, other pages, etc.) and it is possible that brand posts get "lost" in the pile without being seen. Therefore, an additional important question in terms of scheduling of content shared on Facebook brand pages is timing.

Previous studies over temporal interaction patterns showed that most of the user activities on Facebook are undertaken during workdays (Golder et al. 2007, pp. 41-66). In addition, a study on online advertisement reported that the volume of CTR drops significantly over the weekend (Rutz and Bucklin 2008, pp. 87-102). Thus fans are more likely to engage with brand pages over the workdays. Therefore, the following hypothesis is formulated:

H6: Posts created on workdays result in higher level of engagement.

8.2.4. Brand Community Participation

User participation in brand communities on social media was found to increase the brand loyalty (Algesheimer et al. 2005, pp. 19-34; Jahn and Kunz 2012, pp. 344-361). In marketing theory, brand loyalty is approached from two perspectives: attitudinal and behavioral (Oliver 1999, pp. 33-44; Dick and Basu 1994, pp. 99-114). The attitudinal component of loyalty, as a desire to maintain a relationship with the brand, can be measured through the number of interactions with the brand, while behavioral component can be measured by repeated purchase behavior (Jahn and Kunz 2012, pp. 344-361).

Further, brand loyalty was found to have a positive effect on the WOM communication (Hallowell, 1996, pp. 27-42; McAlexander et al. 2002, pp. 38-54). In turn, WOM communication drives community growth (Keller 2007, pp. 448-452), thus indirectly increasing the brand awareness, measured by the community size (Godes and Mayzlin 2004, pp. 545-560; Hoffman and Fodor 2010, pp. 41-49; Keller 2007, pp. 448-452). Thus, engaged fans on brand pages would act as brand advocates, which will attract new members to the community. Previous discussion can be summarized in the form of the following hypotheses:

H7: Loyalty is positively related to the level of engagement.

H8: The volume of WOM communication is positively related to the loyalty.

H9: Community growth is positively related to the WOM volume.

8.2.5. Community Size

Research in sociology showed that community size has a negative effect over the interactions between individuals (Simmel and Wolff 1950). Moreover, membership in larger communities often serves functional purposes, as opposed to friendship and socialization, which are the main motives for participation in small communities (Wellman et al. 1996, pp. 213-238).

In the domain of brand communities, participation in smaller communities results in stronger interpersonal relationships and a greater intention for social engagement (Dholakia et al. 2004, pp. 241-263). Thus, members of small communities are likely to be more connected to the brand community, which would result in higher levels of engagement. Similar results were already presented in the Chapter 6: “Patterns of Interaction on Facebook Brand Pages”. Therefore the following hypothesis is proposed:

H10: Engagement and interactions are negatively related to the community size.

8.2.6. Control Variable: Page Focus

Apart from the factors extracted from the existing theories presented above, an additional control variable was added: *Page Focus*. This variable aims to distinguish among pages created for the brand as a whole, thus fostering communication about the whole product range, and those pages that focus on a single product.

8.3. Method

8.3.1. Data Collection

The dataset used in this study is the same as already described in Chapter 7.2.1: "Dataset". Therefore no additional elaboration will be provided here.

8.3.2. Operationalization of the Variables

8.3.2.1. Dependent Variables

For the translation of marketing constructs to metrics relevant for SMM on Facebook the coding scheme proposed by Hoffman and Fodor (2010, pp. 41-49) was followed.

Brand Engagement

As already discussed in the Chapter 7: "Customer Engagement on Facebook Brand Pages", the official measure for brand engagement on a Facebook brand page, i.e. the Feedback Rate, is not a suitable measure for the engagement on a post level, since (1) it is based on the number of impressions and as such it might be inaccurate, (2) does not include the sharing activity and (3) provides an aggregation of activities on a daily basis instead on the post basis.

To overcome this problem and define a measure of post level engagement, based on the discussion presented in Chapter 7: "Customer Engagement on Facebook Brand Pages", a modification of the Feedback Rate is proposed using the previously defined formulas for likes ratio (see Formula (6)), comments ratio (see Formula (7)) and shares ratio (see Formula (8)). Thus, the calculation of the total brand engagement was performed using the following formula:

$$\text{EngagementRate} = \frac{\#\text{Likes} + \#\text{Comments} + \#\text{Shares}}{\#\text{Fans}} \quad (10)$$

This approach is already accepted by practitioners as a good measure for engagement on a post level[58].

To calculate the engagement on a page level, an average value of engagement rate per post per day was used.

In addition to engagement over moderator posts, and in order to estimate the level of interaction between the fans themselves, the engagement rate over the posts created by the fans was used.

Finally, since the above measures only reflect the number of likes, comments and shares, the average number of posts per fan was added as a measure for brand engagement in order to address the posting activity.

Brand Loyalty

Operationalization of the concept of loyalty for the domain of a Facebook brand page was based on the previous discussion over the measurement of loyalty components through interactions with the brand and returning customers. Making an analogy to the returning customers, the number of returning posters was used as a measure for brand page loyalty.

Word-of-Mouth

Word-of-mouth on a Facebook brand page can be measured through the official Facebook metric *People Talking About This Rate*[59] (PTATR). This measure reflects all created stories, such as posting, responding to event, liking, commenting, etc.

To evaluate possible effect over the valence of WOM communication, the percentage of user posts which contain positive, negative and neutral sentiment was used. Assignment of sentiment to posts was based on utilization of the SentiStrength tool, suitable for analysis of specific content type shared on social media platforms (Thelwall et al. 2012, pp. 163-173).

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58 Formulas revealed: The Facebook and Twitter Engagement Rate. http://www.socialbakers.com/blog/467-formulas-revealed-the-facebook-and-twitter-engagement-rate/. Accessed 2012-06-26

59 People Talking About This Defined. http://www.insidefacebook.com/2012/01/10/people-talking-about-this-defined/. Accessed 2012-06-12

Growth

To calculate the fan growth rate over the observed period, the following formula (11) based on the number of fans was used:

$$\text{GrowthRate} = \frac{\#\text{Fans}(t2) - \#\text{Fans}(t1)}{\#\text{Fans}(t1)} \quad (11)$$

In formula (11), t1 corresponds to the first day of observed period, while t2 to the last.

8.3.2.2. Independent Variables

Vividness

Vividness was coded into four different levels (no, low, medium and high) which correspond to categorizations used in previous studies (Fortin and Dholakia 2005, pp. 387-396; De Vries et al. 2012, pp. 83-91). These levels correspond to the post media type, which in turn reflect the actual content creation undertaken by the page moderator within a Facebook page. At the time of writing, Facebook offers the possibility to share: (1) status which is a plain text and was coded as "no" vividness, (2) photo (low), (3) link to a web page (medium) and (4) video (high).

Interactivity

As already mentioned, for Facebook brand pages a distinction can be made between: (1) page interactivity, and (2) post interactivity.

On the page level, "high" interactivity was assigned to pages which allow fans to post and "low" to those that prevent posting.

In case of post interactivity, "no" interactivity level as assigned to statuses and photos, while "high" interactivity was assigned to links and videos, since these two could be "clicked on" by the fans to view the complete content, i.e. read the text behind the provided link or view the video.

Scheduling

Operationalization of the posting frequency was based on the calculation of the average number of posts per day. Further, in order to extract ranges of frequencies from these values, e.g. posting less than once per day, once per day, etc., a rounded value was taken.

For the posting day, a distinction was made between "weekend" posts, created on Saturday and Sunday, and "workday" posts.

Content Categorization

Content categorization was based on manual coding of the posts, following the coding development strategy proposed by Glaser and Strauss (1967).

Informative posts were written in the form of traditional advertisements, thus containing information about specific products, brand or the company, e.g.:

> *"Spice up your breakfast with our new Cinnamon Streusel Cakes, available now in single serve!" (Original)*

The *Entertaining* category of posts included those written in a form of teaser, slogan, or word play. Most of those posts explicitly asked for engagement from fans, e.g.:

> *"Fill in the blank: Today would be perfect if _____." (Original)*

Finally, posts referring to the Facebook brand page itself, such as declaring the number of fans, were coded as *Community Success*, e.g.:

> *"Imagine 18,000,000 Pringles; that's a LOT of Pringles! But 18,000,000 fans? WOW! Thank you to each and every one of you!"*

Community size

To apply the community size as factor, the average value of fans over the observed interval was calculated.

8.3.3. Data Analysis

Testing of the hypotheses concerning the brand engagement over moderator posts (H1-H6) was based on the Generalized Linear Model regression. The selection of this approach was based on the fact that the selected dependent variables, i.e. number of likes, comments, shares and total engagement as a sum of the previous three, represent count variables with a Poisson distribution (Cameron and Trivedi 1998). In addition, since the distribution variance and mean were found to be different for all of the dependent variables (see Appendix II), a Negative Binomial estimation method was applied since it overcomes the problem of overdispersed data (Cameron and Trivedi 1998). Therefore the model to explain the engagement over moderator posts can be expressed as:

$$
\begin{aligned}
&\log(\text{Engagement Rate}) = \\
&= \log\left(\frac{\#\text{Likes} + \#\text{Comments} + \#\text{Shares}}{\#\text{Fans}}\right) = \\
&= \log(\#\text{Likes} + \#\text{Comments} + \#\text{Shares}) - \log(\#\text{Fans}) = \\
&= \alpha_0 + \alpha_1(\text{entertainment}) + \alpha_2(\text{information}) + \alpha_3(\text{communitySuccess}) \\
&+ \sum_i \alpha_{4i}(\text{vividness \& interactivity}) + \alpha_5(\text{pageInteractivity}) \\
&+ \sum_i \alpha_{6i}(\text{frequency}) + \alpha_7(\text{workday}) + \alpha_8(\text{pageFocus}) + \alpha_9(\text{length})
\end{aligned}
\tag{12}
$$

In the formula (12), *entertainment*, *information* and *communitySuccess* represent dummy variables indicating whether a post contains the particular type of content or not. Similarly, *vividness&interactivity* and *frequency* indicate the presence of a particular rank level in the post. Further, *pageInteractivity* is a dummy variable indicating that a page has high interactivity; *workday* indicates that a post was created on workday and *pageFocus* indicates that the page focuses on the brand as a whole. Finally, *length* represents the number of characters in the post, normalized with log function.

For modeling the individual actions undertaken by the fans, i.e. liking, commenting and sharing, the same formula was used.

For the remaining hypotheses (H7-H10), first a Spearman correlation analysis was used to confirm the existence and evaluate the degree of relationship between the variables.

8.4. Results

8.4.1. Descriptive Statistics

With regards to shared content, posts containing *Entertainment* were most frequently used by page moderators (2948, 58% of total). These were followed by *Informative* posts with 698 occurrences (13.9%), while posts referring to *Community Success* were present in less than 1% of the posts (30 occurrences).

In terms of media type, posts in form of *photos*, corresponding to low vividness and low interactivity, were the most frequently used (2032, 40.4%), while *videos*, corresponding to high vividness and high interactivity, were the least common form of content created by page moderators (473,9.4%).

Furthermore, most of the moderator posts were created on *workdays* (4047, 80.4%). Finally, the average post *length* (*M*) was 120.81 characters with large variations between individual posts (*SD* = 112.14).

Details of the presented categorical variables are provided in Appendix IV.

On page level, 93 (93%) Facebook brand pages used communication policy which allows fans to post on the page wall, thus having a high level of page interactivity.

Further, 58 (58%) of the pages targeted the brand as a whole, while 42 (42%) focused on particular product.

Finally, on the largest number of pages, 44 (44%), moderators posted less than once per day, followed by 38 (38%) of the pages, where posting was done on a daily basis. The number of those who posted more than twice per day (with maximum 4 posts per day) was only 2 (2%) in the observed dataset.

Details of the page level categorical variables are provided in Appendix V.

Finally, a comparison of the difference between engagement rate over posts created by the moderator and those created by the fans on a page level was performed (see Appendix VI for details). A Mann-Whitney test showed that engagement rate over moderator posts (M = 0.000592, SD = 0.000746) is significantly larger (U = 390.0, p < 0.001, r = 0.796) compared to the engagement rate over fan posts (M = 0.000001978, SD = 0.000006366).

8.4.2. Model Evaluation

Evaluation of the proposed model was divided into two elements (1) evaluation of the effect of the elements of moderator posting strategy over the level of engagement over individual posts, and (2) evaluation of the proposed relations between the level of engagement, loyalty, WOM, growth and community size.

The continuation of this section details the obtained results.

8.4.2.1. Factors Influencing the Level of Engagement

Empirical results obtained from the estimation of the proposed model for engagement over moderator posts are presented Table XVIII.

In addition, details of the effect of each factor over the model are provided in Appendix VII.

Table XVIII: Estimation results for engagement rate over moderator posts

		ln(Engagement)		ln(Likes)		ln(Comments)		ln(Shares)	
		B	*Std. Err.*	*B*	*Std. Err.*	*B*	*Std. Err.*	*B*	*Std. Err.*
(Intercept)		-7.797**	0.130	-7.926**	0.131	-11.118**	0.151	-9.381**	0.269
Entertainment	Yes	0.708**	0.045	0.656**	0.045	0.998**	0.054	0.397**	0.089
	No	0a		0a		0a		0a	
Information	Yes	0.256**	0.055	0.286**	0.056	0.318**	0.065	0.066	0.108
	No	0a		0a		0a		0a	
Community Success	Yes	0.453*	0.214	0.561*	0.215	0.110	0.250	0.155	0.423
	No	0a		0a		0a		0a	
Vividness and Interactivity	Photo V=Low I = Low	0.764**	0.054	0.742**	0.054	0.775**	0.064	1.025**	0.109
	Status V=No I=Low	0.369**	0.058	0.310**	0.058	0.874**	0.068	-1.030**	0.109
	Video V=High I=High	0.290**	0.069	0.258**	0.069	-0.078	0.082	1.125**	0.141
	Link V=Medium I=High	0a		0a		0a		0a	
Page Interactivity	High	0.061	0.063	0.032	0.063	0.412**	0.073	-0.416*	0.134
	Low	0a		0a		0a		0a	
Frequency	>2posts/day	0.041	0.077	0.109	0.077	-0.558**	0.087	0.092	0.157
	2 posts/day	-0.352**	0.053	-0.388**	0.053	-0.052	0.062	-0.886**	0.111
	1 post/day	-0.266**	0.051	-0.297**	0.051	-0.022	0.059	-0.878**	0.104
	<1 post/day	0a		0a		0a		0a	
Workday	Yes	-0.006	0.041	-0.077	0.041	0.232**	0.048	0.025	0.082
	No	0a		0a		0a		0a	

		ln(Engagement)		ln(Likes)		ln(Comments)		ln(Shares)	
		B	*Std. Err.*	*B*	*Std. Err.*	*B*	*Std. Err.*	*B*	*Std. Err.*
Page Focus	Brand	0.348**	0.037	0.245**	0.038	0.715**	0.042	0.680**	0.086
	Product	0a		0a		0a		0a	
Post Length		-0.140**	0.016	-0.120**	0.016	-0.089**	0.019	-0.252**	0.026
(Scale)		1b		1b		1b		1b	
(Negative binomial)		1.319	0.023	1.333	0.023	1.730	0.030	5.003	0.106
Likelihood Ratio Chi-Square		1031.653**		946.789**		1443.191**		1190.778**	
Log Likelihood		-40239.534		-38865.367		-30487.478		-19979.261	
Deviance / df		1.204		1.204		1.237		1.036	

* p < 0.05, ** p < 0.0001

a. Set to zero because this parameter is redundant.

b. Fixed at the displayed value.

Entertainment

As shown in Table XVIII, in terms of content contained within the moderator posts *Entertainment* was found to be a significant factor for all engagement measures which increases the number of likes ($\alpha 1$ = 0.656, p < 0.001), comments ($\alpha 1$ = 0.998, p < 0.001), shares ($\alpha 1$ = 0.397, p < 0.001) and total engagement ($\alpha 1$ = 0.708, p < 0.001). The observed effect was found to be strongest for the number of comments. These results provide support for the hypothesis H1a.

Information

Further, providing *Information* was found to increase the number of likes ($\alpha 2$ = 0.286, p < 0.001) and comments ($\alpha 2$ = 0.318, p < 0.001), but does not have an effect over the number of shares. However, it still increases the total brand engagement over moderator posts ($\alpha 2$ = 0.256, p < 0.001), which represents a support for the hypothesis H1b.

Community Success

Finally, posts referring to *Community Success* were found to increase the total level of engagement over moderator posts ($\alpha 3$ = 0.453, $p < 0.05$), as a support to the H1c. It should be noted that this effect originates only from the increase in the number of likes ($\alpha 3$ = 0.561, $p < 0.05$), while for commenting and sharing activities there are no significant effects.

Vividness and Interactivity

In terms of *Vividness & Interactivity*, i.e. the post media type, the results indicate that compared to *links*, which correspond to medium vividness and high interactivity, taken as a baseline for the model, *videos*, which have same interactivity level (high), but higher vividness, result in a higher level of total engagement ($\alpha 4_{video}$ = 0.290, $p < 0.001$). Further, *status* posts, which have a low level of interactivity and no vividness, were found to cause greater level of total engagement compared to *links* and *videos* ($\alpha 4_{status}$ = 0.369, $p < 0.001$). Finally, the greatest effect was obtained for the *photos* ($\alpha 4_{photo}$ = 0.764, $p < 0.001$), which have the same level of interactivity as *status* updates (low), but higher level of vividness (low). These results can be summarized by pointing out the following: of posts with same level of interactivity, those with higher level of vividness cause higher level of engagement. This result supports the hypothesis H2a.

In addition, posts with lower level of interactivity result in higher level of engagement (*photos* and *statuses* versus *videos* and *links*) which is contradictory to H2b. Thus H2b is not supported.

Looking at the effects of *Vividness and Interactivity* on individual activity level, i.e. in terms of liking, comment and sharing, it can be seen that same effect occurs for the number of likes over moderator posts ($\alpha 4_{video}$ = 0.258, $p < 0.001$; $\alpha 4_{status}$ = 0.310, $p < 0.001$; $\alpha 4_{photo}$ = 0.742, $p < 0.001$). In the case of commenting, interactivity has the same negative effect as on overall level. Still, there is a difference in the effect caused by the level of vividness, i.e. there is no significant difference found between engagement over *links* and *videos*, while engagement over *photos* ($\alpha 4_{photo}$ = 0.775, $p < 0.001$) is lower compared to the engagement over *status* posts ($\alpha 4_{status}$ = 0.874, $p < 0.001$). Finally, in terms of sharing, vividness shows the same positive effect, i.e. for the same level of interactivity, posts with higher level of vividness cause greater level of engagement. In terms of interactivity the effect differs, i.e. *status* posts are the least frequently shared media type ($\alpha 4_{status}$ = -1.030, $p < 0.001$), while *photos* and *videos* cause similar positive effect compared to *links* as baseline ($\alpha 4_{photo}$ = 1.025, $p < 0.001$; $\alpha 4_{video}$ = 1.125, $p < 0.001$).

Page Interactivity

Page Interactivity as a factor did not show significant effect over the total level of engagement, as well as over the number of likes. Significant and positive effect was found to exist over the number of comments ($\alpha 5$ = 0.412, p < 0.001). However, in terms of sharing, the effect was negative ($\alpha 5$ = -0.416, p < 0.05). Since these results contradict each other, and there is no effect on total engagement, the hypothesis H3 cannot be confirmed.

Post Length

Post Length was found to have a negative effect over all engagement measures, likes ($\alpha 9$ = -0.120, p < 0.001), comments ($\alpha 9$ = -0.089, p < 0.001), shares ($\alpha 9$ = -0.252, p < 0.001) and total engagement ($\alpha 9$ = -0.140, p < 0.001). These results comply with the hypothesis H4.

Posting Frequency

In terms of *Posting Frequency*, posting level of *less than once per day* was taken as a baseline for comparison. As can be seen from Table XVIII, pages that posted *once per day* received lower level of total engagement compared to the baseline ($\alpha 6_{\text{one post per day}}$ = -0.266, p < 0.001). Further, those pages that posted *twice per day* caused lower level of engagement compared to both, baseline and *once per day* ($\alpha 6_{\textit{two posts per day}}$ = -0.352, p < 0.001). The coefficient for *more than twice per day* was not found to be significant. On individual activity level, in the case of liking ($\alpha 6_{\textit{one post per day}}$ = -0.297, p < 0.001; $\alpha 6_{\textit{two posts per day}}$ = -0.388, p < 0.001) and sharing ($\alpha 6_{\textit{one post per day}}$ = -0.878, p < 0.001; $\alpha 6_{\textit{two posts per day}}$ = -0.886, p < 0.001) similar results were obtained. For the commenting activity, only the coefficient for posting more than twice per day was found to be significant for the model, again showing a lower level of activity compared to the baseline ($\alpha 6_{\textit{more than two post per day}}$ = -0.558, p < 0.001). Thus on individual activity level, the same effect as the one obtained for the total engagement occurred. These results indicate that higher posting frequency has a negative effect over the level of engagement as a support for hypothesis H5.

Workday

Workday was not found to be a significant factor for the total level of engagement. The only significant and positive effect that occurs is over the number of comments ($\alpha 7$ = 0.232, p < 0.001). Thus, hypothesis H6 is only partially supported.

Page Focus

Finally, the control variable *Page Focus* was found to have a significant effect, i.e. pages that focus on *brand in total* receive more attention from fans compared to brands that focus on *individual products*. This effect occurs for

total engagement ($\alpha 8$ = 0.348, p < 0.001), and also for number of likes ($\alpha 8$ = 0.245, p < 0.001), comments ($\alpha 8$ = 0.715, p < 0.001) and shares ($\alpha 8$ = 0.680, p < 0.001). In addition, the effect was found to be strongest for the number of comments.

8.4.2.2. Effects of Brand Engagement and Community Size

To test the hypotheses H7 to H10 the results obtained from the Spearman correlation analysis were used. The complete correlation table is provided in Appendix VIII.

Effect of the Brand Engagement over Loyalty

Looking at the obtained results it can be seen that there is a positive correlation between the percentage of returning fans, as a brand loyalty measure, and the engagement rate over moderator posts (r(98) = 0.250, p < 0.05). In addition, similar results were obtained for the engagement rate over fan posts (r(98) = 0.577, p < 0.01) and number of posts per fan (r(98) = 0.754, p < 0.01). These findings support the hypothesis H7.

Effect of the Loyalty over Word-of-Mouth Communication

Looking at the *People Talking About That Rate*, as a measure for the volume of WOM communication, it can be seen that there is a positive correlation to the percentage of returning fans, as a measure for brand loyalty (r(98) = 0.267, p < 0.01). This result supports the hypothesis H8.

Effect of the Word-of-Mouth Communication over Community Growth

A positive correlation was also found to exist between the *People Talking About That Rate* and the growth rate (r(98) = 0.896, p < 0.01) confirming the expected outcome as proposed in hypothesis H9.

Effect of the Community Size over Brand Engagement

Finally, a negative correlation was found to exist between the community size and the engagement rate over fan posts as a measure for interaction among the fans (r(98) = -0.769, p < 0.01), but also over the number of fan posts (r(98) = -0.402, p < 0.01) and the engagement over moderator posts (r(98) = -0.291, p < 0.01). These results provide support for hypothesis H10.

Factors Influencing the Word-of-Mouth Valence

In addition to the volume of WOM communication, the possible correlation between the brand loyalty and WOM valence was investigated. This analysis was conducted by looking into the percentage of posts containing positive, negative and neutral sentiment. The results indicate that correlation only exists between the percentage of returning fans and the percentage of negative (r(98) = 0.396, p < 0.01) and neutral (r(98) = 0.208, p < 0.05) posts, while there

is no correlation to the percentage of positive fan posts. However, a direct positive correlation between the engagement and the WOM valence was found to exist. Engagement rate over fan posts shows a positive correlation to both, percentage of positive ($r(98) = 0.336$, $p < 0.01$) and negative fan posts ($r(98) = 0.262$, $p < 0.01$). Similarly, number of fan posts has a positive correlation to the percentage of positive ($r(98) = 0.210$, $p < 0.05$) and negative ($r(98) = 0.372$, $p < 0.01$) fan posts.

In terms of the possible effect of the valence of WOM communication over the growth rate, surprisingly, a negative correlation was found to exist for the percentage of positive fan posts ($r(98) = -0.217$, $p < 0.01$) and a positive correlation to the percentage of neutral fan posts ($r(98) = 0.218$, $p < 0.05$).

A summary of the results presented in this section in terms of the supported hypotheses is provided in Table XIX.

Table XIX: Summary of the estimation results for the proposed model showing supported and non-supported hypotheses

Hypothesis	Effect	Expected	Obtained	Result
H1a	Entertainment -> Engagement	(+)	(+)	Supported
H1b	Information -> Engagement	(+)	(+)	Supported
H1c	Community Success -> Engagement	(+)	(+)	Supported
H2a	Vividness -> Engagement	(+)	(+)	Supported
H2b	Post Interactivity -> Engagement	(+)	(-)	Not Supported
H3	Page Interactivity -> Engagement	(-)	(+) comments (-) sharing	Not supported
H4	Length -> Engagement	(-)	(-)	Supported
H5	Frequency -> Engagement	(-)	(-)	Supported
H6	Workday -> Engagement	(+)	(+) comments	Partially supported
H7	Engagement -> Loyalty	(+)	(+)	Supported
H8	Loyalty -> WOM	(+)	(+)	Supported
H9	WOM-> Growth	(+)	(+)	Supported
H10	Community Size -> Engagement	(-)	(-)	Supported

8.5. Discussion and Managerial Implications

The results presented in the previous section prove that different components of SMM posting strategies for moderators of Facebook brand pages have an effect on the engagement level of the fans.

8.5.1. Content

Content was confirmed to be an important element of the moderator strategy which can significantly increase the level of engagement. *Entertaining* content was found to be the most influential in terms of total fan engagement, by increasing the engagement on all three individual levels - liking, commenting and sharing. The largest effect of entertaining content was found to exist over the commenting activity. This could be explained by looking at the form of these posts, a large fraction of which asks for direct feedback or response.

Although not frequently used by page moderators, posts referring to *Community Success* result in significant increase in the total engagement, but mainly through the increase of the number of likes.

Similarly, posts offering brand or product related *Information* increase the total level of engagement through liking and commenting, but do not cause an effect on the number of shares. This could be explained by the fact that community, product or brand related content is probably considered to be specific and is perceived as valuable within the community itself. As such, it might lose its significance when shared by the fans on their own walls, to their friends outside the community who might not be interested in that particular brand.

Previous discussion can be summarized in the form of two managerial implications:

> *I1A: Facebook brand page moderators should create content that provides Entertainment and Information, but also make references to the Community Success in order to increase the level of engagement.*
>
> *I1B: Facebook brand page moderators should post Entertaining content in order to increase volume of the WOM communication and the reach of their message, by stimulating the sharing activity.*

8.5.2. Media Type

Media type was also found to be an important element of the posting strategies. Through the chosen media type practitioners have the possibility to address the concepts of *Vividness* and *Interactivity* which were already found to be important factors for advertisements. Since these two constructs are contained within the same post feature, on Facebook brand pages *Vividness* and *Interactivity* should be addressed from the perspective of finding the optimal combination, as already proposed by Fortin and Dholakia (2005, pp. 387-396).

Results presented in previous section showed that on overall level, *photos*, with low interactivity and low vividness, have caused the greatest level of engagement, followed by *status* posts (low interactivity, no vividness), then *videos* (high interactivity, high vividness) and finally *links* (high interactivity, medium vividness). These results indicate that interactivity has a stronger effect over the engagement level, resulting in content with higher level of vividness (*links* and *videos*) to be perceived as less attractive compared content with lower level of vividness (*photos* and *statuses*) due to the higher interactivity. These results might be due to the fact that highly interactive content, *links* and *videos*, require larger amount of time to be consumed, compared to *photos* and *statuses*. In addition, *links* also cause a redirection to another web page thus exposing the fan to additional amount of content to be seen. If the presented content does not meet the expectations of the fan, he will most likely stop reading or watching the *video*, and in addition, no further engagement will occur on the Facebook brand page.

Looking at the individual engagement measures, liking shows the same order of media type preference as on the overall level. In the case of sharing there is a slight difference, while photo, video and link posts maintain their order, status posts display the lowest level of sharing. This behavior might be due to the fact that fans may feel that content with higher level of vividness could be more appealing to their friends compared to plain text. Finally, in terms of commenting, while interactivity exhibits the same negative effect, the effect of vividness differs from the expected behavior. In particular, photos which have higher level of vividness received less attention compared to status posts which have lower level of vividness. This effect might be due to the fact that within the observed dataset, majority of status posts contain *Entertaining* content (1591, 86% of status posts, 32% of total) which was already shown to have a significant effect over the level of commenting.

The previous discussion can be summarized in the form of the following managerial implications:

> *I2A: Facebook brand page moderators should create less interactive content (i.e. photos and status updates), in order to increase the total level of engagement.*
>
> *I2B: Facebook brand page moderators should focus on vivid content, i.e. videos, photos and links in order to increase the reach of their message, thus also the volume of WOM communication, by stimulating the sharing activity of the fans.*

8.5.3. Length

Post length was also confirmed to be an important factor which has a negative effect over the total level of engagement, as well as on each of the individual activities. The origin for this effect can be further supported by the concept of information overload (Jones et al. 2008, pp. 323-332). Thus the following implication can be drawn:

> *I3: Facebook brand page moderators should post shorter content in order to increase the total level of engagement.*

8.5.4. Posting Weekday

Opposite to what was expected, posting weekday was not found to be an important factor. Positive effect occurs only over the commenting activity. Since commenting requires more time than liking and sharing (which only require one click), it can be assumed that people are willing to spend this time on the days when they use Facebook with greater intensity, i.e. on the workdays. Thus despite the fact that the proposed hypothesis was not fully supported, still the following recommendation can be given:

> *I4: Facebook brand page moderators should post on workdays in order to increase the number of comments.*

8.5.5. Frequency

Posting frequency was proven to be an important element of the posting strategy which significantly influences the level of engagement. The results indicate that higher posting frequency has a negative effect on the level of engagement in total, but also on individual activities. In addition, within the

analyzed dataset, posting up to once per day was found to cause the highest level of user engagement. It should be noted that in the case of commenting, the only significant effect that occurred was for posting more than twice per day. As in the case of length as a factor, this finding can also be explained by the concept of information overload (Jones et al. 2008, pp. 323-32). Thus, based on the presented results the following implications can be formulated:

I5A: Facebook brand page moderators should post up to once per day in order to receive the highest level of engagement.

I5B: Posting more than once per day would decrease the total level of engagement.

I5C: Posting more than twice per day will significantly decrease the number of comments.

8.5.6. Communication Policy

The communication policy established by the company determines the page interactivity, and allows or prevents creation of fan posts on the wall. This was not found to be a significant factor for the engagement over moderator posts. The only positive effect occurred over the commenting activity. In addition, a negative effect was found to exist over the sharing activity. A possible explanation could be found by looking at the media type of the posts as a factor that influences the sharing action, i.e. pages with low interactivity posted more vivid content, 86% (340 posts out of 394) as opposed to 61% (2853 of 4641) on the highly interactive pages. Still, in order to fully understand this effect a further investigation is required.

Based on the obtained results a strong implication regarding the communication policy cannot be derived. Still, the following recommendations can be given:

I6A: Companies should create highly interactive Facebook brand pages in order to increase the WOM volume through fan posts.

I6B: Our results proved that highly interactive Facebook brand pages receive more comments.

8.5.7. Page Focus

The control variable used in this study, i.e. the page focus, was found to be an important factor for the level of engagement on Facebook brand pages. The

results presented in the previous section showed that those pages that foster communication over the brand, instead of focusing on a single product, receive more attention from their fans. These results were obtained for all engagement measures with the strongest effect over the number of comments. This could be explained by the fact that more products in the range would satisfy different interests/tastes, thus increasing the level of engagement. Therefore, the following implication can be derived:

> *I7: Companies should create Facebook brand pages for the brand as a whole instead of focusing on a single product, in order to increase the level of engagement.*

It should be noted that some of the findings differ from the ones obtained in a similar study conducted by De Vries et al. (2012, pp. 83-91) over a smaller dataset (355 moderator posts from 11 Facebook brand pages). For example, providing informative content was not shown to be a significant factor for engagement, while entertaining content was found to have an effect only over the number of likes. Further, posting day was also not found to have a significant effect over the engagement and finally, vividness and interactivity were shown to only partially influence the engagement, yet not with the expected effect of increasing it.

This difference originates from the operationalization of the engagement construct, i.e. De Vries et al. (2012, pp. 83-91) do not normalize the number of likes and comments with the number of fans, although they also report a large variation in the number of fans for the observed dataset. The approach used in this study was already accepted by the practitioners as a suitable method for engagement measurement in the Facebook environment where there is a great variance in terms of community size among different brand pages (see Appendix VI for details).

In addition, in the study conducted by De Vries et al. (2012, pp. 83-91), vividness and interactivity were coded in a way that does not distinguish between media type and content. Still, as shown in the previous discussion, separating these two post features provides a clearer approach towards formulating guidelines for practitioners.

Finally, the frequency as a factor was addressed by the top position of the post on the brand page. Still, we believe that referring to previous findings from the field of online advertisement in terms of the effect of the advertisement position is not suitable for Facebook as a platform since majority of the fans consume the content posted by the brand page on their profile wall and only a

small proportion of post impressions is made by actually visiting the page. This opinion is also adopted by the practitioners who show interest in frequency of posting as influencing factor as already mentioned in the example provided in Chapter 1.1.3.2: “Lack of Established Strategies”.

8.5.8. Engagement as a Factor

In addition to evaluating the factors that influence the engagement over moderator posts, this study reveals how and to which extent engagement can further influence additional marketing objectives, such as brand loyalty, WOM communication and community growth, indirectly leading towards increased brand awareness (Hoffman and Fodor 2010, pp. 41-49).

To translate these marketing objectives into the domain of a Facebook brand page, the number of returning fans was proposed as a measure for brand loyalty. In addition, the established Facebook’s measure *People Talking About That Rate* was proposed as a measure for the volume of WOM communication and finally. Results presented in previous section confirmed the existence of a positive correlation between these marketing constructs as proposed by the model. These findings indicate that a carefully planned SMM strategy, which would result in high level of user engagement, could lead towards increasing of the community size, used as a measure for successful utilization of Facebook brand pages. Therefore:

> *I8: Facebook brand page moderators should prepare strategies that increase the level of engagement, which in turn will increase the number of loyal users, the volume of WOM communication and ultimately, the number of fans.*

Further, it was shown that an increased level of engagement could lead to an increased number of opinionated posts, both with positive and negative sentiment. It is interesting to note that this only applies to the engagement over the fan posts and number of posts created by the users, while it does not apply to the engagement over the moderator posts, which is not correlated to the WOM valence. In addition, the number of user posts is positively correlated with the engagement over moderator posts, thus once again, increasing the engagement over moderator posts could lead to increased WOM valence. Thus:

> *I9: Facebook brand page moderators should prepare strategies that increase the level of engagement, which in turn will increase the percentage of positive user posts.*

8.5.9. Community Size as a Factor

Finally, the community size was proven to have a negative correlation to the engagement level. This, in particular, applies to the interactions between individuals, measured through the engagement of fan posts. In addition, engagement over moderator posts is significantly larger compared to the engagement of fan posts. Since the value of interaction between fans for the WOM valence was already pointed out, the following recommendation can be given:

> *I10: With the growth of community size, Facebook brand page moderators should undertake more active approach in order to encourage interactions between the fans.*

8.6. Summary, Limitations and Future Work

This study proposed a coherent model which explains (1) the relation between individual content characteristics as factors that influence the level of brand engagement, and (2) the relation between engagement and (a) loyalty, (b) WOM communication, (c) growth and (d) community size.

To translate the classical marketing constructs into the domain of a Facebook brand page, two measures for brand engagement were proposed, i.e. number of likes, comments and shares over moderator posts as a ratio to number of fans, and number of posts created by the fans. Further an analogy was made between the returning customers and returning fans to operationalize the concept of brand loyalty. Finally, the official Facebook measure, *People Talking About That Rate* was applied as a measure for the volume of WOM communication. The proposed model was empirically evaluated, based on the large dataset consisted of all activities over two months on the top 100 Facebook brand pages in the Food/Beverages category.

The presented results confirmed that providing entertaining and informative content within posts significantly increases the level of engagement. In addition, fans positively react to content referring to community success. It was further shown that vividness increases, while interactivity decreases the level of engagement over moderator posts, making photos the most appealing post media type. In addition, lengthy posts are not well received by the fans. Posts should not be created more than once per day in order to receive the optimal engagement, and when created on workdays it will increase the level of comments. Finally, pages should focus on the brand in total, instead of focusing on individual products and should allow fans to post on their walls.

It was further proven that increasing the level of engagement is a worthy goal since it leads towards increased brand loyalty, WOM volume and valence and community growth. These findings should encourage moderators of Facebook brand pages to prepare clear posting strategies that trigger the activity of fans and drive adoption in the long run.

The results presented in this paper are limited to the *Food/Beverages* Facebook brand page category. In order to confirm these findings or identify specific industry domains that display different behavior this analysis should be expanded to posts gathered from other categories of Facebook brand pages. In addition, in order to improve the prediction models, an investigation of the existence of additional factors that might influence the level of engagement, loyalty, WOM communication and awareness should be performed, including components of marketing campaigns outside the Facebook brand page itself.

Summary of Main Findings

- Returning fans can be used as a measure for brand loyalty on Facebook brand pages.
- The official Facebook measure, *People Talking About That Rate*, can be used a measure for the WOM volume.
- Content that provides entertainment and brand related information, as well as references to the community success increase the level of engagement on Facebook brand pages.
- Highly interactive content (i.e. links and videos) decrease the total level of engagement.
- Vivid content, i.e. videos, photos and links increase the reach of the marketing message, thus also the volume of WOM communication.
- Posting on workdays increases the number of comments.
- Lower posting frequency (up to once per day) results in higher level of engagement.
- Communication policy which allows posting on the wall increases the WOM volume through fan posts and comments.
- Focusing on the brand as a whole instead on a single product increases the level of engagement.
- Engagement over moderator posts increases the number of loyal fans, the WOM volume and the number of fans.
- Engagement over moderator posts increases the percentage of positive user posts.
- The community size has a negative effect over the level of engagement.

9. Evaluation Framework for Social Media Brand Presence

The framework presented in this chapter addresses the research question RQ10: “How to evaluate the effectiveness of social media marketing?” presented in Chapter 1.2.1.4: "Effectiveness Evaluation” and represents an outcome of the previous chapters. It builds upon the recognized research gaps and the specific questions, raised by the scholars and practitioners in the domain of utilization of social media for marketing purposes (see Chapter 2: “Related Work” for details). Further, it summarizes the methods used for the analysis of the data described in the previous chapters (see Chapter 4 to Chapter 8 for details), and proposes specific steps to be undertaken by the company to provide evaluation of the effectiveness of their SMM campaigns. Finally, a relevance of the results of application of the proposed methods for the specific elements of SMM strategies is discussed, based on the previously presented results (see Chapter 4 to Chapter 8 for details).

The content presented in this chapter was submitted for publication to the “Social Network Analysis and Mining” journal under the title “Evaluation Framework for Social Media Brand Presence” (Pletikosa Cvijikj et al. 2013a). This section contains excerpts from the referenced publication which are not further demarcated in the text.

9.1. Introduction

The growing popularity of social media in the business environment, measured by the number of existing and emerging brand channels across various platforms and the number of members of these online brand communities, has turned the question from “whether to engage in social media marketing” to “how to engage on SMM platforms” and “how to measure the effectiveness of the undertaken efforts” (Stelzner 2012). Still, on account of the newness of

SMM, in an attempt to establish the communication with their customers, companies mostly experiment with many different forms of interaction.

An additional difficulty for effectiveness evaluation originates from the fact that most of the existing efforts are still based on traditional marketing measures, such as increase in sales or market share. These measures are not suitable for the social media environment and should be replaced with those that focus on objectives such as increasing the brand awareness, engagement and WOM communication on these platforms (Hoffman and Fodor 2010, pp. 41-49). Similarly, Owyang (2010) suggests the modification of the structure of a ROI pyramid for social media, as illustrated on Figure 43.

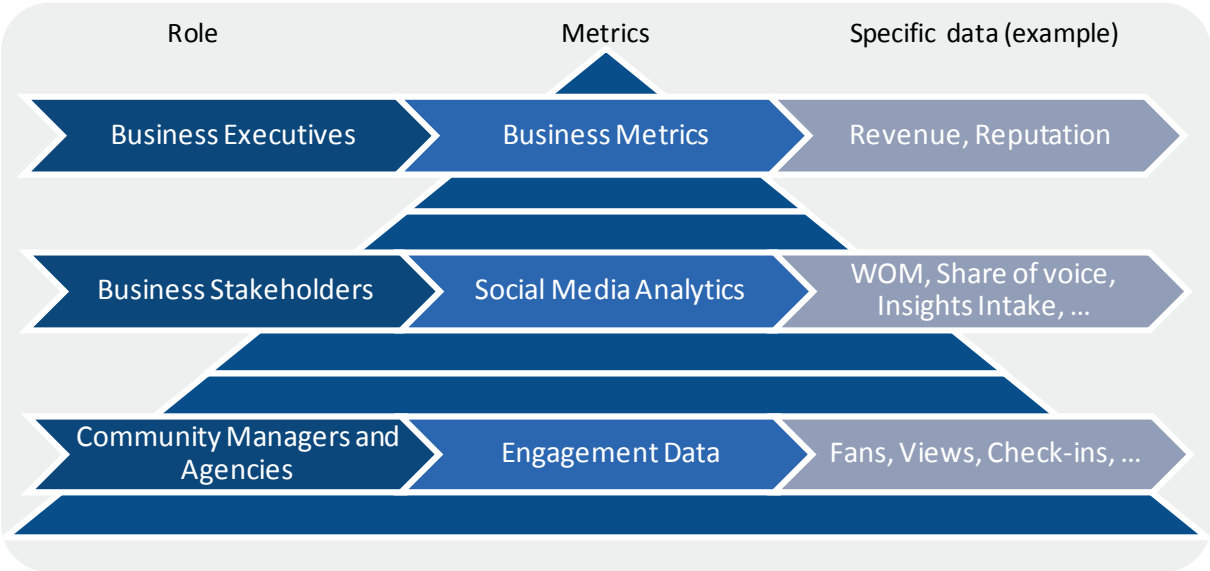

Figure 43: The social media return-on-investment pyramid (Owyang 2010)

It can be seen that the social media analytics, measured through non-financial marketing objectives, such as the WOM communication, has the central position in the process of effectiveness evaluation. These metrics are further based on the engagement data, measured through the number of fans or undertaken actions, as a basic element of the social media ROI pyramid.

The relatively simple structure of the proposed ROI pyramid does not simplify the process of selection of the appropriate metrics which still represents a challenge for the practitioners[60]. For example, a number of members of a brand community, commonly used as a success criteria, is only a partial

[60] Metrics Mess: Five Sad Truths about Measurement Right Now. http://adage.com/article/digital/metrics-mess-sad-truths-online-measurement/149055/. Accessed 2012-08-07

representative of the effectiveness of a brand page while, as already shown in previous studies and in the results presented in Chapter 6: “Patterns of Interaction on Facebook Brand Pages”, only a small portion of the community members actively engage on social media platforms. Instead, the majority of participants represent passive fans, i.e. lurkers.

Despite the variations in the recommendations given as a result of the ongoing attempt to determine the most appropriate methods and measures for effectiveness evaluation of SMM campaigns, both, practitioners and scholars agree that continuous measurements and iterative adjustment of SMM strategies is the right way to approach the problem of establishing a successful brand presence on social media platforms (Dubach Spiegler 2011; Hoffman and Fodor 2010, pp. 41-49).

To contribute in this direction, this chapter introduces an evaluation framework that allows companies to set up and then perform continuous monitoring of the content and activities on their SMM channels.

9.2. Effectiveness Evaluation of Social Media Marketing

This section explains the concept of the evaluation framework for social media brand presence. Based on the recognized problem and the state of the art approach presented in the previous section, a conclusion is drawn that a well defined evaluation framework is needed for utilizing SNs as a platform for SMM.

9.2.1. Justification

From the discussion on social media utilization for marketing purposes presented in Chapter 2: “Related Work”, the following statements are selected as arguments for justification of the proposed solution:

- 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 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 has been recognized as 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 shared posts. In turn, obtained results could be used to adjust the company's social media 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.

To justify the selection of the framework components, a summary of the findings and recommendations from the previous work in the field relevant for the effectiveness evaluation is contained within the following list:

- Building an engagement plan as a part of the social media strategy should start by focusing on the ongoing conversation (Li 2007a). In addition, it should be taken in consideration that the communication on social media platforms is affected by the type of offered product or service, resulting in variety of discussed topics on different social media platforms. Therefore, the first step towards understanding the conversation should be classification of different types of content (Kozinets et al. 2010, pp. 71-89).

- The next step for creation of the engagement plan is finding out what interactions, content, and features will keep users coming back (De Vries et al. 2012, p. 83-91; 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 2008). 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, pp. 89-103). As a result, companies and scholars are trying to define the "best" social media strategies based on the insights from existing examples and trial-and-error experiences (Coon 2010). Still, as Wilson et al. (2012, pp. 211) point out, "these few studies only begin to touch on ways in which Facebook can be used to connect with customers." To avoid mistakes, benchmarking to similar brand channels, competitors or "best players" could bring valuable insights.

- The final aspect to be investigated while performing the evaluation of the effectiveness of utilization of social media platforms for marketing purposes derives from the core element of social media - 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, pp. 219-229) as an important component for optimization of the SMM efforts.

Based on these statements, an evaluation framework for social media brand presence is proposed in continuation.

9.2.2. Evaluation Framework for Social Media Brand Presence

The reasoning presented in the previous section clearly indicates a need for a framework which could be used by the companies for evaluation of effectiveness of the undertaken marketing initiatives on social media platforms. In addition, based on the previously provided justification and the proven value of the individual analysis steps presented in previous chapters of this thesis, the following components of the evaluation framework are proposed:

- **Analysis of users.** 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 can help companies increase the overall level of engagement on their social media channels (Li 2007b; Parent et al. 2011, pp. 219-229).

- **Analysis of the user-generated content.** 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, pp. 89-103). In addition, monitoring general trends enables brand image monitoring and buzz listening (Goorha and Ungar 2010, pp. 57-64; Kasper and Kett 2011, pp. 662-669).

- **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 content that causes the greatest level of interaction (De Vries et al. 2012, pp. 83-91; Li 2007b). This could help companies increase the level of engagement which in turn could result in optimization of the marketing investment (Sterne 2008) through increasing the loyalty (Jahn and Kunz 2012, pp. 344-361), WOM communication (McAlexander et al. 2002, pp. 38-54) and indirectly brand awareness, by influencing the community growth (Godes and Mayzlin 2004, pp. 545-560; Hoffman and Fodor 2010, pp. 41-49; Keller 2007, pp. 448-452) as already shown in Chapter 8: "Increasing Engagement, Loyalty, Word-of-Mouth and Growth on Facebook Brand Pages".

- **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 Figure 44.

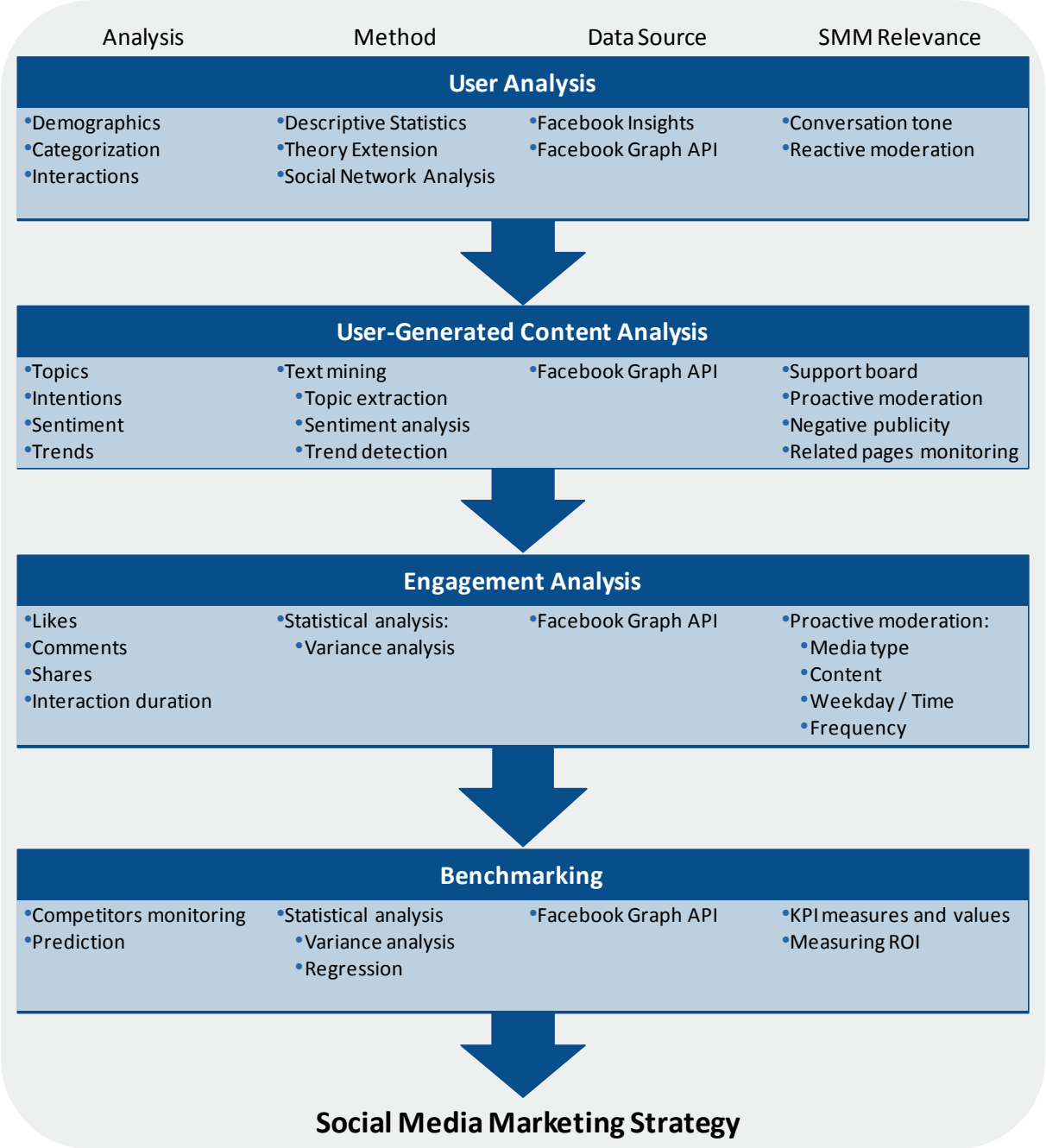

Figure 44: Evaluation framework for social media brand presence with four components requiring specific actions for effectiveness evaluation

In the continuation, each component of the proposed framework is described in details, focusing on the (1) data source, (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.

9.3. Framework Components

This section provides a description of each of the proposed components of the evaluation framework, focusing on the: (1) performed analysis, (2) data collection, (3) the method and (3) relevance for SMM.

9.3.1. User Analysis

User analysis should focus on three elements: (1) demographics, (2) user categorization and (3) interactions between the users. Details of each step are provided in the continuation of this section.

9.3.1.1. Demographics

Demographics data of the brand community on Facebook provides a possibility to gain a 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 Facebook Graph API by default. These could be received as a response to the following query:

```
http://graph.facebook.com/<USER_ID>
```

where the *USER_ID* is a unique identification of a Facebook user, and should be known in advance. Thus, demographics data provided through the Graph API will only be available for the active fans, whose *USER_ID* can be obtained from the created post, comment or like. At the same time, the lurkers' demographics will remain unknown. For each fan, the data that can be retrieved by default contains only: (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. An illustration of the response obtained from the above query is given in Listing 2.

Listing 2: Example of *User* object returned by the Facebook Graph API

```
{
   "id": "1610800649",
   "name": "Jan Keim",
   "first_name": "Jan",
   "last_name": "Keim",
   "gender": "male",
   "locale": "de_DE"
}
```

In turn, Facebook Insights offers the demographics data only in an aggregated format, allowing access to (1) gender and age distribution, (2) language, and (3) geographical distribution, i.e. cities and countries. These values are provided for the whole community (see Figure 9 for an illustration of the available output). 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 enabling distinction between the demographics of the active fans and those that do not engage on the brand page, i.e. lurkers.

It should be stressed again, that the data provided by the Facebook Insights platform is available only to the brand page moderators. Thus companies cannot collect aggregated demographics data from other brand pages, such as related pages or those of their competitors.

Method

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

A system that provides 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, based on the Graph API, into a designated database on a regular (daily) basis, and
- Collection and storage of demographic data for each fan which engaged over the brand page by posting, commenting, liking or sharing.

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, the more appropriate approach to these values would be to use them to adjust the tone of the conversation to the known participants on this communication medium.

This section clearly shows that demographics data on Facebook is relatively limited and covers only small number of details. To gain further understanding of the users, a categorization is useful.

9.3.1.2. User Categorization

As already explained in Chapter 6: "Patterns of Interaction on Facebook Brand Pages", Facebook fans could be divided into the following five categories based on the interaction patterns: (1) *Lurkers*, (2) *Posters*, (3) *Sharers*, (4) *Commenters* and (5) *Likers*. The detailed description of the characteristics of each of the proposed categories is already presented and will not be elaborated further.

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

Data Source

The data available from Facebook 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 page wall, by issuing the following query:

```
https://graph.facebook.com/<PAGE_ID>/feed?access_token=<ACCESS_TO
KEN>
```

As already explained in Chapter 3.4: "Available Data Sources on Facebook", the *Feed* connection of the *Page* 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 fan, (4) likes (number and fan details), (5) comments, (6) shares, (7) application used for posting, (8) creation time and (9) time of last interaction. The format of the obtained response is illustrated in Appendix XI.

For the analysis performed in this evaluation step, of interest is the posting fan, represented within the "*from*" tag.

Further, to obtain the list of all *Commenters* and *Likers*, for each of the obtained posts two additional sub-queries should be issued:

```
https://graph.facebook.com/<POST_ID>/comments?access_token=<ACCES
S_TOKEN>
```

```
https://graph.facebook.com/<POST_ID>/likes?access_token=<ACCESS_T
OKEN>
```

where the first query returns a list of all comments over the post, including the fan who wrote the comment, while the second query returns a list of all fans who liked the post.

Method

As already mentioned in Chapter 6.3.1: "Categorization of Fans Based on Interaction Patterns", categorization of the brand page fans represents 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 data does not require a particular method. Again, results of the descriptive statistics can provide insights into the patterns of interaction on a Facebook brand page.

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 different 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, and 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

This categorization is important for the companies in order to understand how their customers use the social media platform, in order to develop appropriate communication strategies through proactive moderation. 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 fan's friends and on his profile page, thus extending the reach of the marketing message, liking and commenting only appear 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, automatically measuring 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 should 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 the WOM objectives (Harris and Rae, 2009, pp. 24-31).

9.3.1.3. Interaction Analysis

An additional view on the user activities and interactions should be given from the perspective of social network analysis (SNA) in order to understand the characteristics of the brand community by shaping a network of interactions between the moderator and the users.

Data Source

Categorization of the users on Facebook brand pages, described in the previous section ("User Categorization") was based on the patterns of undertaken interactions, i.e. posting, liking, comment and sharing. Thus, interaction analysis between the fans is based on the same data.

Method

The method proposed for this evaluation step is dynamic social network analysis (DSNA) which provides the possibility for temporal visualization of the network structure and measures, i.e. visualization of the network evolution over time (see Chapter 6: "Patterns of Interaction on Facebook Brand Pages" for details).

Interaction network is created by using fans as network nodes and 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 shared by the users are addressed to the moderator, thus the resulting

network has a perfect star shape and as such provides no insights. Specific measures from SNA theory which should be applied include: (1) betweenness centrality, (2) degree centrality and (3) group density. These measures are already explained in details and will not be elaborated further.

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 and its integration with an existing DSNA tool which could perform the interaction analysis on regular time intervals. A simple database query could extract the network structure and feed it to the DSNA tool. Moreover, an alarm could be triggered in the case when the interaction drops beneath the threshold value which can be chosen based on the outcome of the benchmarking component (see Chapter 9.3.4: "Benchmarking" for details).

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. network hubs. Both of these should be encouraged to engage within the brand page since: (a) if a fan representing 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.

The results of the DSNA presented in Chapter 6: "Patterns of Interaction on Facebook Brand Pages" revealed that the increase in the community size results in decrease of the engagement level. This complies with existing theories on brand community participation and was further confirmed through the results of the correlation analysis presented in Chapter 8: "Increasing Engagement, Loyalty, Word-of-Mouth and Growth on Facebook Brand Pages". Thus the proposed approach provides the opportunity to identify the critical point 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).

9.3.2. User-Generated Content Analysis

In order to successfully run a Facebook brand page as a part of the SMM approach, marketing departments 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 posts shared by the page fans on a company's brand page, and (2) analysis of the UGC contained in a form of Facebook public posts, i.e. trend monitoring.

9.3.2.1. Content Analysis over Brand Pages

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

Data Source

The data available from Facebook Graph API provides the possibility to understand the content created by the fans on the brand pages. This can be achieved by collecting posts generated by the fans on the page wall, by issuing the following query:

```
https://graph.facebook.com/<PAGE_ID>/feed?access_token=<ACCESS_TOKEN>
```

As already explained in Chapter 3.4: "Available Data Sources on Facebook", the *Feed* connection of the *Page* object represents a list of all *Post* objects shared on the page wall. The format of the obtained response is illustrated in Appendix XI. For the analysis performed in this evaluation step, of interest is

the content contained within the created message, represented with the "*message"* tag of the JSON object.

Method

Research in the fields of opinion mining and sentiment analysis enables automatic identification and extraction of attitudes, opinions, and sentiment 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 differs from the formal written language that such analysis tools are optimized for (Yassine and Hajj 2010, pp. 1136-1142).

To overcome these challenges, the action-object approach is more suitable for analysis of posts from a company's brand page, as an accurate classification method. The action-object approach for post classification (Zhang and Jansen 2008, pp. 414–433) represents a manual process of text analysis, following the coding development strategy (Glaser and Strauss 1967). The process consists of three steps: (1) coding strategy development, (2) coding and (3) integrating. A detailed description of each step of the process is provided in Chapter 4: "User Generated Content on Facebook Brand Pages" and will not be further elaborated here.

It should be noted that 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 simple approach would be to begin with manual analysis and then apply the tagged dataset as a training set to some of the existing learning algorithms. 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) analysing 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, locations with great volume of sales, existing problems and perceived competitors, this analysis opens the opportunity for product development by focusing on the large fraction (27%) of the posts belonging to the *Requests & Suggestions* category (see Chapter 4: "User Generated Content on Facebook Brand Pages" for details).

From the SMM perspective, topics and intentions analysis reveals the types of content which require 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[61], answers should 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. Obtained results indicate the need for experts in (1) sales, (2) logistics, (3) company/brand information, (4) product information, and (5) environmental issues. 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, thus exposing the company to possible fan loss such as in the case of Swiss company Mammut[62].

Furthermore, since the topics and intentions for participation in brand communities were shown to be 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. An example that continuous monitoring and an appropriate reaction can prevent fan loss, and even result in

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61 In The Social Media And Digital World, Brands Can't Take A Sick Day. http://crowdshifter.com/2012/02/23/in-the-social-media-and-digital-world-brands-cant-take-a-sick-day/#.UCIQhqPwV8E. Accessed 2012-08-08

62 Umweltaktivist gegen Mammut: Angriff am Gipfel. http://bernetblog.ch/2011/11/29/umweltaktivist-gegen-mammut-angriff-am-gipfel/. Accessed 2012-07-17

community growth is the one of Toyota and their "social-media response room" on Facebook, after the massive recall in 2010[63].

9.3.2.2. 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 the Facebook users on their 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 conversation from the related pages, pages of known competitors, but also on the underlying platform as a whole in a form of trend or buzz monitoring.

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 stream. Instead, similar but limited functionality is available through the search feature, returning a list of public posts for a given keyword upon a query with the following format:

```
https://graph.facebook.com/search?q=<KEYWORD>&type=post&limit=<NL>
&access_token=<ACCESS_TOKEN>
```

It should be noted that although not required, adding the *ACCESS_TOKEN* parameter to the query expands the response array from lists of posts shared only in the geographical region to those shared globally.

In order to collect all the public posts, a simple algorithm which performs a search, taking each ASCII character as a keyword, thus providing a loop of 26 search queries, should be applied. In addition, within each loop several steps might be performed, depending on the number of existing posts, due to the limited length of the resulting array defined through the *NL* parameter in the query. Finally, the process should be repeated on regular and short intervals for continuous data collection.

For the analysis performed in this evaluation step, of interest is the content contained within the created message, represented with the "*message*" tag of

63 The Cult of Toyota. Available at: http://adage.com/article/news/social-media-cult-toyota/142335/. Accessed 2012-08-06

the JSON object. Posts containing special characters, such as those written in Cyrillic, Chinese, etc., appear in the obtained response in Unicode format. Thus, these will be collected with the proposed approach (at least for the *KEYWORD=u*), but an additional step would be required to transform them back to their original format and extract their meaning.

Details of the applied algorithm for data collection and tuning parameters, such as the collection interval and number of posts collected in a single query are described in Chapter 5: "Monitoring Trends on Facebook" and will not be elaborated here further.

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, pp. 11–21). 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 is proposed (Mathioudakis and Koudas 2010, pp. 1155-1158). In addition, when calculating the term frequency, only one occurrence of a term per post should be counted. This adjustment overcomes the situation when a term which appears multiple times in a same post will be ranked higher in the list compared to a term which appears in several different posts.

Once the weighted list is created a clustering of the terms that belong to the same topic can be done by (1) distribution – to eliminate the multiple occurrences of the lexically similar n-grams with different lengths belonging to the same posts, and (2) co-occurrence – to group the terms that frequently appear in same posts, assuming that they refer to the same topic. Detailed description of the proposed method is provided in Chapter 5: "Monitoring Trends on Facebook".

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 the 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 interaction over 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. As such, buzz monitoring is supported by numerous existing free and commercial solutions as already elaborated in Chapter 3.5.1: "Measurement and Monitoring of Marketing Efforts". Trend monitoring algorithms provide 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.

9.3.3. 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 user 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 more user interaction, 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 fan engagement. This can be achieved by collecting posts created by the page moderator, by issuing the following query:

```
https://graph.facebook.com/<PAGE_ID>/posts?access_token=<ACCESS_TOKEN>
```

The *Posts* connection of the *Page* is similar to the *Feed* connection. It also represents a list of *Post* objects but is limited only to those posts which were created by the page moderator.

Each of the obtained *Post* objects contains the following relevant information: (1) post content ("*message*" tag), (2) post media type ("*type*"), (3) number of likes (*"likes" : "count"*), (4) number of comments (*"comments" : "count"),* (5) number of shares (*"shares" : "count"*), (6) creation time *("created_time"*) and (7) time of last interaction *("updated_time"*). The format of the obtained response is illustrated in Appendix XI.

Method

As already explained in Chapter 7: "Customer Engagement on Facebook Brand Pages", in order to answer the questions which content results in the highest level of engagement, the following two steps should initially be performed: (1) defining a categorization rules for the moderator posts by identifying the features that distinguish different posts, and (2) defining measures for user interaction over the posts shared by the page moderators.

Post Categorization. Posts shared by the moderator on Facebook can be categorized by (1) media type and (2) content. Post media type corresponds to the sharing action undertaken by the page moderator. Facebook brand pages offer the possibility to share: (1) status, (2) photo, (3) video, and (4) link. 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, a generalization of the topics in a form of a topic category representation is proposed. The categorization presented in Chapter 7 was performed manually. Since the moderators are those creating the content with a particular goal in mind, assigning categories to own posts wouldn't require a great effort. Still, for expanding the analysis over additional brand pages, automation of the topic extraction would increase the effectiveness of the proposed method. A simple keyword based categorization algorithm could result in increased effectiveness of the proposed method.

In addition to the content, the time of posting is a factor that might influence the interaction level, including the posting weekday. Since brand posts appear on the walls of profile pages on Facebook users, determining the optimal time for posting, when the marketing message is most likely to be seen could also result in increased engagement over the post.

Engagement Measurement. As already described in Section 3: "Facebook as a Platform for Social Media Marketing", apart from allowing users to post, Facebook offers the possibility to comment, like or share the posts created on the page wall. Based on this, the number of comments, likes and shares can be used as a precise measure for the level of user 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 comments, likes and shares should be normalized with the number of page fans at the moment, in order to enable the possibility to compare the engagement level over longer time interval, but also to the engagement on other brand pages which might have different community size. Finally, interaction duration can be used by page moderators as an important measure for planning of the posting frequency.

Statistical Data Analysis. 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 through the 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 Mann-Whitney test with Holm's sequential Bonferroni correction (Holm 1979, pp. 65-70). 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

As already mentioned in Chapter 7, engagement is the new key metrics for success of SMM campaigns, leading to the growing popularity of concepts such as *Return-on-Interactions* and *Return-on-Engagement*. In order to increase the level of engagement, companies need to find out what interactions, content, and features will keep fans coming back. The outcome of such analysis, i.e. the list of content characteristic which result in the highest level of fan engagement, represents a direct input for planning the posting strategy on Facebook brand pages.

The method proposed in this evaluation step enables measurement of the engagement level on Facebook brand pages over the content created by the company on the level of individual post through the number of undertaken actions, i.e. likes, comments and shares, and interaction duration.

Further, the method proposes four basic factors which influence the level of engagement over posts created by the moderator on Facebook brand pages: (1) media type, (2) content type, (3) posting day and (4) time.

The obtained results of the study presented in Chapter 7 showed that *photos* are the media type that triggers the largest level of engagement while *links* result in the least engagement from the fans. In addition, while *status* posts result in higher volume of comments, multimedia types (*photos*, *videos*, *links*) are those that are being shared, thus increasing the volume of WOM communication.

In terms of the content category, posts referring to *Fans No*, *Engagement Boosters* and *Advertisements* were found to be the most popular among the page fans.

Further, on Facebook brand pages fans engage in higher volume over posts created on *weekdays* compared to those created on *weekends*.

Finally, posts created in the morning and early afternoon cause the largest level of user engagement.

These findings can be used as clear and specific guidelines for the moderator posting strategies.

9.3.4. 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 of similar brand pages. Apart from the known competitors, a company can gain additional valuable insights by learning from the "best practice" examples on the underlying SN platform outside of the company's industry. In case of Facebook, identification of the biggest players can be done by utilizing some of the existing platforms, such as already mentioned Fan Page List (see Chapter 7.2.1: "Dataset" for details), which provide page ranking based on different criteria, such as number of fans and growth rate. 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

The 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 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 type, (3) region, (4) nationality, and (5) target group, but also in terms of interaction strategy such as (6) posting policy, (7) style of interaction (posting or commenting only), (8) comment type and (9) frequency, (10) community size, and (11) 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 provide the possibility for creation of structural models which can be used to clarify the relations between the

traditional marketing constructs. Structural equation modelling (SEM) allows for both, confirmatory and exploratory modelling. As such this approach is suitable for the field of SMM where there are many questions still to be answered due to the differences in the marketing communication compared to traditional one-to-many communication. The created model can further be used by the companies for prediction of the values of the relevant metrics based on the undertaken actions.

The results presented in Chapter 8: "Increasing Engagement, Loyalty, Word-of-Mouth and Growth on Facebook Brand Pages" confirmed that a relation between the main marketing goals, such as brand engagement, loyalty, valence and volume of WOM communication and the community growth exists also on brand pages as platforms for marketing. The proposed model supports the idea that the content posted by page moderators on a Facebook brand page which satisfies particular user needs and is designed well (see Chapter 8 for details) leads to higher level of user engagement, which in turn, results into higher level of brand loyalty, thus also indirectly increasing brand awareness.

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 growth rate of number of fans across the brand pages on the underlying platform?
- What is the average number of posts created by the fans over the selected time interval?
- 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 content more than once?

- What is the most commonly used posting frequency by the moderators?
- Which posting frequency results in the highest level of engagement?
- When do moderators post in terms of time of day and day of week?
- 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 on the selected social media platform?
- What is the most commonly used moderation style?
- What is the most commonly practiced communication policy on the underlying platform?
- 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 the entertainment celebrities, which also show remarkable results measured by the number of fans.

Statistical analysis of the obtained numbers provides insights into the influencing factors that increase the brand page effectiveness in terms of engagement level, 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, collected from the best players on the underlying social media platform, provides the possibility to prepare the initial communication and posting strategy. 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.

9.4. Summary, Limitations and Future Work

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, an evaluation framework was proposed which allows monitoring and measuring of the effectiveness of SN utilization for marketing purposes. A detailed description of specific methods to be used for each of the identified actions to be undertaken during the evaluation process was given. The value of the obtained results was discussed for SMM practitioners from the perspective of planning the moderation policy:

- **User analysis** provides insights into the demographics of the users which can be used as an indication of the brand's demographics, but also to adjust the tone of the conversation to the known participants. In addition, it provides the possibility to categorize, measure and improve the level of user's activities by encouraging posters and preventing aggressive and mocking comments. Moreover, by understanding the nature of the "superfans", an opportunity for targeted marketing appears. Further, the proposed method provides the possibility to identify the most important members of the community, the bridges and the hubs in the network. Finally, a critical point when the interactions start to decline, due to community growth, can be identified and reacted upon.

- **User-generated content analysis** shows clearly what types of questions and comments require responses from the moderator. In addition, it indicates a need for a "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. By listening to the conversation, a company could gather ideas for new products and services which are perceived as needed by users themselves. Finally, listening to the broader conversation provides the possibility for brand image monitoring, finding out who the brand advocates are, and identifying the opportunities to revert dissatisfied customers.

- **Engagement analysis** shows clear evidence that it is possible to increase the level of engagement of fans on brand pages by carefully planning the posting strategy which in turn is considered as a new measure for effectiveness of SMM campaigns. The proposed analysis reveals the media types and topic categories of posts created by page moderators that attract the attention of majority of the users, resulting in increased level of engagement. This in turn should potentially result in increased community size through the effect of the WOM marketing. In addition, the proposed method provides the possibility to choose the most appropriate time for posting. Finally, the posting frequency can be planned based on the estimated interaction duration.

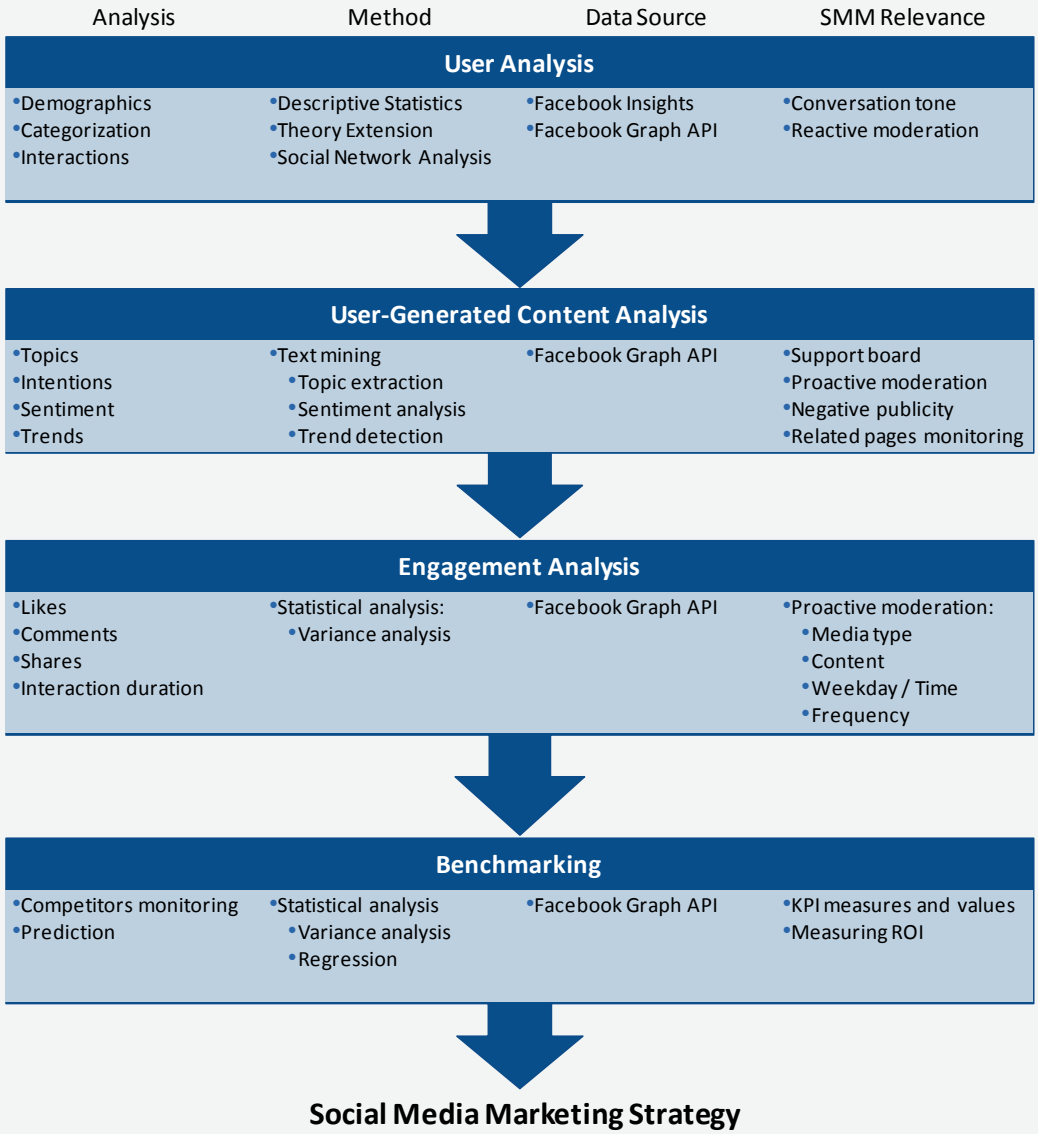
- **Benchmarking** provides an alternative view on a brand's efforts with SMM by monitoring the competitors' or leading brand sites. For this purpose, gathering data from related brand pages can provide valuable data against which to benchmark the brand's efforts, and they can be used to identify successful brand pages whose moderating style or practices can be emulated. In addition, obtained insights can be used to define the desired KPI values to be set as SMM goals. The proposed method also provides the possibility to generate a model which can be used to predict marketing objectives such as engagement level, volume and valence of WOM communication, loyalty of fans on brand pages, and community growth, which directly results in increased brand awareness on social media platforms.

This chapter demonstrated that by following a structured process a company's brand page can be systematically evaluated. Setting measurement criteria, gathering data and performing analysis at set intervals will allow a company to monitor and improve their SMM efforts. The chapter'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.

The terminology and methods described in this chapter reflect the choice of Facebook as an underlying social media platform, which might be considered as a main limitation. Still, it is important to note, that the concepts presented, such as fans, social connections, messages or moderation, are basic to any SN, thus the proposed framework is generic enough to be translated to emerging or future SN platforms. 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 easily added is the next step to be undertaken. In addition, this system should provide the possibility to select and configure the available engagement modes and specific content characteristics relevant for the selected social media platform.

Summary of Main Findings

- Formulating objectives and providing information systems to measure the relevant metrics is necessary for controlling the marketing efforts on social media platforms. This can be achieved by establishing an evaluation framework consisted of the following components:



10. Conclusions

Social media marketing is a new and fast emerging element of companies' integrated marketing communications. While there are still many unanswered questions on how to utilize social media for marketing purposes, the growing number of those companies who have embraced social media is making a pressure on those who still try to evaluate the potentials or the possible harm it could bring to the company and the brand.

One way to support the companies in decision making is to provide answers to their questions by revealing the value that social media platforms could bring to the companies. This can be done by relating the new concepts of social interactions and consumer-lead discussions to some of the traditional marketing constructs, such as WOM, loyalty, brand image and awareness, but also to recently recognized benefits of online platforms, such as UGC and viral marketing. These insights can be used by companies to select KPI measures which are aligned with their goals and to perform continuous monitoring of the effectiveness of their efforts, which in turn enables avoiding the possible harm by timely reaction to negative feedback.

The work presented in this thesis provides a contribution in this direction by answering the following research question:

How to evaluate the effectiveness of social media marketing?

Based on the literature review, specific problem domains were recognized, and sub-questions were formulated:

- RQ1: What are the topics of conversation?
- RQ2: What are the intentions for participation in brand communities on social media?
- RQ3: Which emotions are shared within the UGC and how?

- RQ4: How to monitor trends over the UGC on social media?
- RQ5: What are the characteristics of trending topics?
- RQ6: What are the interaction patterns on social media platforms?
- RQ7: What are the characteristics of the social network created between the users of social media platforms?
- RQ8: Which factors influence the level of engagement on SMM platforms?
- RQ9: What is the relation between the engagement, loyalty, word-of-mouth and growth on SMM platforms?
- RQ10: How to evaluate the effectiveness of social media marketing?

These questions were further used as motivation for five empirical studies, which were conducted as a part of this thesis.

Based on the results obtained from these studies and the confirmed value of the applied methods for achieving a goal of aligning the social media concepts to marketing objectives, an evaluation framework was proposed. This framework provides a detailed explanation of the steps to be undertaken for effectiveness evaluation. In addition, it reveals the relevance of the proposed steps and the obtained results for social media practitioners in terms of planning the SMM strategy.

To provide greater details on the contributions of this thesis, the continuation of this section discusses the implications of the results obtained through the conducted studies, as well as those of the proposed evaluation framework, for the relevant research fields. Finally, a discussion on the implications of this thesis for marketing practitioners is provided as an equally valuable contribution.

10.1.Implications for Research

From the literature review presented in Chapter 2: “Related Work”, five research fields, relevant for the research question answered in this thesis, were identified: (1) social media platforms and social networks, (2) brand communities, (3) word-of-mouth and viral marketing, (4) user-generated content, and (5) social media marketing. Individual contributions of this thesis

for each of these research fields are presented in the continuation of this section.

10.1.1. Social Networks

As already presented in Chapter 2: “Related Work”, social media platforms and SNs have already been a subject of excessive academic research. This thesis brings a contribution to this field by focusing on a social network created between the members of Facebook brand pages. In particular, the following issues were addressed: (1) usage patterns, (2) social interactions, and (3) usage motivations. Most important, this thesis closes the gap of lack of studies regarding the usage of social networks for establishing B2C interactions.

Results presented in Chapter 6: “Patterns of Interaction on Facebook Brand Pages”, contribute by proposing new user categorization, based on the usage patterns. This categorization extends the general distinction of users on online platforms into active users and lurkers, by pointing out to the differences among active users, based on the differences in the available activities to be undertaken, and the level of engagement these activities require. Thus, active users on Facebook can further be divided into: posters, commenters, sharers, and likers. In addition, this study showed that the percentage of lurkers on Facebook brand pages is 98%, which is significantly higher compared to 90%, which is the previously observed number in forums and blogging platforms.

In terms of social interactions, the same study over patterns of interactions contributes to existing knowledge by revealing the structure of the social network created among the members of Facebook brand pages. This study shows that the level of social interactions among the members of the community is very low. This is in particular the case for the commenting over the content created by other fans, while liking is the more adopted form of interaction, resulting in a much larger network of interactions.

Finally, the results presented in Chapter 4: “User Generated Content on Facebook Brand Pages” revealed the main motives for participation on Facebook brand pages which will further be elaborated in the following section in the context of brand community participation, since these two research fields are interconnected in regard to this question.

Finally, in regard to utilization of social networks for B2C communication, a detailed elaboration will be provided in the “Social Media Marketing” section below.

10.1.2. Brand Communities

The research presented in this thesis closes the gap in the field of brand communities by investigating a new form of communities created on Facebook brand pages. The main findings relevant for brand community participation refer to: (1) intentions for participation, (2) the effect of community size, and (3) the relation between the engagement in brand communities and other marketing objectives, such as loyalty, WOM and brand awareness.

The results presented in Chapter 4: "User Generated Content on Facebook Brand Pages" indicate that the main motives for participation in brand communities on Facebook are: (1) providing suggestions and requests about new products or services, (2) expressing affect towards the brand or a specific product, (3) social interaction with the brand and other members of the community, (4) obtaining information related to the brand, (5) complaining and criticism, (6) expressing gratitude to the brand, (7) comparison with competitors, and (8) praise.

In regard to community size as a factor, the results presented in Chapter 6: "Patterns of Interaction on Facebook Brand Pages" showed that community size has a negative correlation with the level of undertaken activities and interactions among members of the community, i.e., as the community grows, members become less active and less connected to each other, making the moderator a central figure. Similarly, Chapter 8: "Increasing Engagement, Loyalty, Word-of-Mouth and Growth on Facebook Brand Pages" showed that engagement level within smaller communities is higher, compared to the engagement level in big communities. These findings confirm the previous findings from the field of brand communities, where participation in smaller communities was found to result in stronger interpersonal relationships and a greater intention for social engagement. In addition, similar results were already observed in the field of sociology for offline communities.

Finally, the model proposed in Chapter 8: "Increasing Engagement, Loyalty, Word-of-Mouth and Growth on Facebook Brand Pages" confirmed that the brand community participation within Facebook brand pages has the same positive effect on consumers' loyalty, valence and volume of WOM communication, and community growth, which in turn leads towards increased brand awareness, as already found to exist in other forms of online brand communities.

10.1.3. Word-of-Mouth and Viral Marketing

This thesis provides contribution in the domain of WOM marketing and closes a gap in regard to understanding the WOM communication lead by consumers on Facebook brand pages. The contributions in this research field are: (1) revealing the motivations for engaging in WOM communication, (2) understanding the consequences of WOM, (3) relevance of WOM for FMCG industry domain, and (4) opportunities for viral marketing.

Motivations for engaging in WOM communication were already presented in the previous section, in the context of participation in brand communities, thus these will not be further elaborated here.

In terms of understanding the consequences of WOM, the results presented in Chapter 8: “Increasing Engagement, Loyalty, Word-of-Mouth and Growth on Facebook Brand Pages” confirmed that the volume of WOM communication is positively correlated to community growth which was already observed on other online platforms. Finally, in Chapter 6: “Patterns of Interaction on Facebook Brand Pages” preliminary insights were presented in regard to the effect of negative WOM on the structure of the social network showing that negative WOM leads to a lower level and a more uniform interaction patterns among fans. This observation requires additional investigation to be confirmed or explained in details.

Further, the work presented in this thesis focuses on the specific industry domain of FMCG. As such, it reveals the specific topics of conversation referred to within the UGC on Facebook brand pages. As already shown in Chapter 4: “User Generated Content on Facebook Brand Pages”, Facebook brand pages are suitable platform for WOM marketing, since users of these platforms mostly talk about the brand, specific products or product features. Moreover, these topics are discussed in the context of expressing sentiment, which usually appears as positive or providing suggestions for new products or features. These findings are in line with the goals of WOM marketing.

Finally, by providing possibility to share content, but also by creating traces after each undertaken action, Facebook provides a suitable platform for viral marketing. In this context, Chapter 7: “Customer Engagement on Facebook Brand Pages” and Chapter 8: “Increasing Engagement, Loyalty, Word-of-Mouth and Growth on Facebook Brand Pages” reveal the factors that might increase the level of engagement, thus increasing the volume of viral marketing.

10.1.4. User-Generated Content and Text Mining

Contributions made in this thesis in the domain of user-generated content are relevant for the field of text mining. These can be divided into two domains: (1) understanding the format of UGC shared on Facebook brand pages, thus providing insights for the field of opinion mining, and (2) providing a solution for monitoring trends on Facebook, which was not previously available.

Each of these contributions is already discussed in the corresponding chapters thus the continuation of this section provides only a summary of implications for research in both domains.

10.1.4.1. Opinion Mining

The analysis of UGC, described in Chapter 4: "User Generated Content on Facebook Brand Pages", provides the possibility to address the challenges of automatic opinion mining by understanding the format of the content shared on Facebook brand pages.

The results obtained in this study confirmed that language used on social networks differs from the one used in blogs and forums. In particular, a more informal communication is used, based on the Internet slang including: (1) slang abbreviations, (2) emoticons and (3) interjections. Thus, for automatic opinion mining, lexicons should be created which would be capable of interpretation of the above listed language elements. Further, the number of emoticons, repeating vocals and punctuation marks can be used as a measure for the sentiment intensity.

10.1.4.2. Monitoring Trends

While monitoring trends has been studied over other social media platforms, such as blogs, forums or the microblogging platform Twitter, Facebook is lagging behind due to the absence of support by the platform provider for continuous and real-time data collection. In addition, privacy policies on Facebook introduce limitations into the amount of available data.

The system described in Chapter 5: "Monitoring Trends on Facebook" represents a first solution which overcomes the problem of data collection and proposes a method for topic extraction from the UGC in a form of public posts shared on Facebook. As such, it provides support to those stakeholders who are interested in using Facebook as a source of information.

Further, based on the obtained results, this study reveals the differences between different topics. Based on the observed differences, a categorization of trending topics is proposed. Finally, in order to increase the understanding

on emerging trends on Facebook, an analysis of the characteristics of the proposed trend categories is provided with a focus on the distribution and information diffusion.

10.1.5. Social Media Marketing

The main contribution of this thesis is the one in the field of social media marketing. A review of existing literature, presented in Chapter 2: "Related Work" pointed to three main gaps in this domain:

- Lack of understanding of the concept and its utilization (Richter et al. 2011, pp. 89-103);
- Lack of empirical studies to confirm the value of undertaken actions (Wilson et al. 2012, pp. 203-220); and
- Lack of established methods for effectiveness evaluation (Dubach Spiegler 2011; Murdough 2009, pp. 94-99).

This thesis provides contribution for each of these domains.

To address the first two domains, i.e. to increase the understanding of the concept of social media marketing and its utilization by both, companies and consumers, empirical studies based on real utilization data were conducted, as already presented in previous chapters of this thesis. These studies were selected based on the identified domains of interest for both, academia and practitioners, derived from the review of academic literature and practitioners reports, including: (1) study of the user-generated content and its value for WOM marketing, (2) proposing a solution for trend identification from UGC on Facebook, (3) study of the usage patterns and its relevance for brand communities and social networks, (4) study of the effects of undertaken actions in terms of volume and form of responses obtained from the community members, and (5) proposing a model which confirms the relation between the engagement in brand communities on social media platforms and marketing objectives such as loyalty, WOM and brand awareness.

As a result, insights and contributions were obtained, which were already elaborated in corresponding sections and some of them also mentioned in previous sections of this chapter, as contributions to the related research fields which are the foundations for social media marketing. These insights can serve as a basis for future examination of SMM activities over other industry domains and social media platforms.

In addition, based on the proven value of these studies, by pointing to the relevance of the obtained results for the domain of social media marketing and in particular for the practitioners, this thesis provides a contribution in the terms of evaluation of effectiveness of marketing efforts on social media platforms, by proposing an evaluation framework presented in Chapter 9: "Evaluation Framework for Social Media Brand Presence". This framework contributes to the academic domain by: (1) pointing out to four different components of effectiveness evaluation based on literature review, (2) specifying the exact methods to be applied for measurement of the effectiveness and (3) revealing the relevance of obtained results for different segments of social media strategies.

10.2.Implications for Practice

Apart from contributing in the domain of academia by closing the recognized research gaps, the results of the studies conducted as a part of this thesis also provide insights for practitioners. These insights were presented in details in a form of managerial implications for each of the conducted studies within the corresponding chapters. The continuation of this section summarizes the main points.

10.2.1. User-Generated Content

In order to successfully run a Facebook brand page as a part of the SMM approach, companies need to understand their users by learning how and why they interact on brand pages. One way to achieve this goal is by looking at the conversation lead by consumers on social media platforms.

The results of the analysis presented in Chapter 4: "User Generated Content on Facebook Brand Pages" confirmed that posts shared on Facebook brand pages represent a valuable source of knowledge for companies, particularly for monitoring the brand image from both, functional and hedonic perspective. In addition, companies can use the UGC as a source of ideas about new products and services. Thus social media platforms can be used for product development.

Organizationally, the variety of referred topics indicates a need for support board behind the moderator. This board should be addressed when a specific question is posed, in order to provide timely answer, as expected by users of social media platforms. Furthermore, the topics and categories, i.e. intentions for participation in brand communities on Facebook, were shown to be

interconnected. Therefore, the topic-category matrix can be used as a tool for measurement of success of SMM utilization over time.

Finally, the results of the sentiment analysis showed that positive sentiment is expressed far more often compared to negative. Since negative publicity is one of the major concerns of the companies, these results confirm that Facebook brand pages are a suitable platform for SMM where majority of user are already fans of the brand. Still, as visible from the examples presented in Chapter 1: “Introduction”, continuous monitoring of sentiment fluctuations is recommended in order to avoid escalation of negative publicity. This could be achieved by fast and appropriate response to possible complaints.

10.2.2. Monitoring Trends

Apart from looking at the activities on their own SMM channels, companies can learn from other existing examples by tracking the activities of competitors and related brand pages, but also by looking at the content shared on user profile pages in the form of public posts. This opens the opportunity to stay in line with competitors, maintain a certain level of control over the related brand pages, and listen to what non-fans have to say about the company and the brand.

Simple buzz monitoring was shown to result in inaccurate numbers by counting the non-related content as a company reference, based on accidental keyword match in the UGC. Trend monitoring provides a solution for overcoming this problem by grouping related content into topic groups which provides more accurate insights into consumers’ interest.

It should be noted that companies should not listen only to the brand related communication. Instead, looking at the topics that attract large fractions of users can help moderators come up with ideas for Entertaining and Informative content which were shown (within this thesis) to attract the attention of brand page fans, resulting in higher level of engagement.

10.2.3. Patterns of Interaction

User categorization based on the performed activities is important for the companies in order to understand how their customers use the social media platform, which in turn could help develop appropriate communication strategies. Continuous monitoring of the activities based on the proposed categorization enables deeper understanding of the level of interactions and its evolution over time.

The results presented in Chapter 6: “Patterns of Interaction on Facebook Brand Pages” show that simple monitoring of the community size is not an appropriate measure for effectiveness of SMM since majority of the brand page fans (98%) are passive users who never contribute by content creation or interaction. In addition, active fans prefer not exposing themselves to possible reactions from other members of the community, thus embracing the “safest” option for interaction, i.e. liking. Since different actions result in different forms of UGC, with “posting” having the highest value (as shown by obtained results from the UGC analysis), companies should try to lead their fans towards the highest level of activity, i.e. posting. This can be achieved by stronger moderation, such as encouraging posters by liking or writing supportive comments over their content, and preventing or discouraging aggressive content.

The proposed approach also provides the possibility to identify the superfans, which represent ideal group for targeted marketing.

Finally, this study showed that the increase of the size of the community requires more active moderation in order to encourage interaction between the fans. This can be achieved by employing a strategy that would incorporate activities such as competitions, polls and discussion threads.

10.2.4. Customer Engagement Factors

Understanding the preferences of fans could enable creation of posting strategies which could increase the hedonic experience on social media platforms, thus increasing the level of engagement on these platforms measured by the number of likes, comments and shares, and interaction duration over the company-communicated content.

The results presented in Chapter 7: “Customer Engagement on Facebook Brand Pages” confirmed that post media type, content category, weekday and time of posting have effect on the engagement level of the fans on a Facebook brand page.

From the media type perspective, photos trigger the largest level of engagement while links result in the least engagement from the fans.

Further, posts containing content which refers to the reached number of fans, those written in a form of engagement boosters - by offering entertaining content or asking a question, and those which offer brand related content in a form of advertisement, result in highest level of engagement.

In regard to the question when the content should be posted, this study shows that content created on workdays triggers higher level of engagement, compared to weekends. Moreover, content created during the morning and early afternoon attracts greater attention of the fans.

10.2.5. Increasing Engagement, Loyalty, WOM and Growth

In order to estimate the ROI of SMM efforts, companies should develop an approach which is suitable for social media platforms. This can be achieved by focusing on the value of social media marketing measured by the level of engagement, which in turn provides opportunity to develop strategies that fit with existing marketing objectives, such as brand engagement, WOM communication and brand awareness.

The results presented in Chapter 9: “Evaluation Framework for Social Media Brand Presence”, expand those obtained in the engagement analysis by proposing a more complex model which confirms that by satisfying the specific needs of consumers on social media platforms, companies could achieve higher level of engagement.

Facebook brand page moderators should create content that provides Entertainment and Information, but should also make references to the Community Success in order to increase the level of engagement. In addition, Entertaining content leads towards higher volume of the WOM communication and increases the reach of the company-communicated content, by stimulating the sharing activity.

Further, Facebook brand page moderators should create less interactive content (i.e. photos and status updates) in order to increase the total level of engagement, while focusing on vivid content, i.e. videos, photos and links would increase the reach of the message, thus also the volume of WOM communication, by stimulating the sharing activity of the fans.

Lengthy posts are not perceived well by fans, thus moderators should create shorter content in order to increase the total level of engagement.

Further, moderators should post up to once per day in order to receive the highest level of engagement. On the contrary, when posting more than once per day, the total level of engagement decreases, while for more than twice per day, the number of comments created by fans will be significantly lower.

In terms of communication policy, companies should allow their fans to post in order to increase the WOM volume through fan posts, but also through the increased number of comments.

Focusing on the brand as a whole instead of focusing on a single product attracts the attention of larger audience, resulting in increased level of engagement.

Apart from giving recommendations which would lead towards greater engagement, this study provides support to the value of the Return-on-Interaction approach, pointing to the fact that level of engagement has a positive influence over the number of loyal fans, the volume of WOM communication and ultimately, the number of fans. In addition, it increases the percentage of positive user posts, thus influencing the brand attitude.

Finally, community size was again found to be a factor which has a negative influence, thus continuous monitoring of growth and engagement should enable recognition of the point in time when engagement starts to decrease, in order to undertake more active approach which would encourage interactions between the fans as already discussed in the interactions section above.

10.2.6. Evaluation Framework for Social Media Brand Presence

As a final outcome, this thesis proposes an evaluation framework which enables monitoring of the effectiveness of marketing efforts on social media platforms. This framework provides a precise description of the steps to be undertaken, data to be used, methods to be applied and the relevance of the obtained results for SMM communication strategies.

Companies should implement tools which integrate the described steps, thus supporting the process automation. These tools should be used to define initial strategies and KPI values to be achieved, based on the analysis of the “best players” on the selected social media platform.

Once the brand page has been launched, the proposed framework would enable continuous monitoring of the marketing efforts and consumers’ responses to the undertaken actions. Based on the obtained results, appropriate interventions can be undertaken in regard to the factors which have a negative influence, such as the community growth, or malicious content created by the fans.

In addition, since brand communities might differ depending on the offered product or service, companies should use the results of the continuous

monitoring to adjust the initial strategies in accordance to the specific characteristics of their own brand communities.

10.3.Limitations and Possible Directions for Future Research

The constraints faced upon this thesis originate from the large amount and variety of social media platforms and industry domains interested in SMM. As a result, this thesis was limited to a single platform and a single industry domain. The limitations and the opportunities for future research which emerge from these limitations are discussed in continuation.

10.3.1. Limitations

As already discussed in Chapter 1: “Introduction”, there are two main limitations of the research conducted in this thesis: (1) selection of Facebook as a social media platform, and (2) selection of Fast-Moving Consumer Goods, as a product category to be studied.

The selection of Facebook 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.

The selection of Fast-Moving Consumer Goods as a product category 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. To maintain consistency in the obtained results, for the further analysis conducted over the larger number of brand pages, the same type of brand was selected.

These two limitations open the opportunities for future research as described in the following section.

10.3.2. Possible Directions for Future Research

The future work on the topic addressed in this thesis could be conducted in three directions: (1) validating and extending the presented results, (2) generalization of the results over different industry domains, and (3) generalization of the results over different social media platforms. Each of the proposed directions is detailed in the continuation.

10.3.2.1. Validating and Extending the Presented Research

Evaluation framework proposed in this thesis is an outcome of (1) identifying domains of interest by reviewing the previous work and reports from practitioners, and (2) conducting studies for each of the identified domains in order to assess the feasibility of this approach and the potential impact on SMM strategies. As such, a practical validation could provide confirmation of its value.

In addition, taking in consideration the fast development of social media platforms, the concepts presented in this thesis 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. For example, according to some preliminary insights, a recently introduced feature known as sponsored stories (see Chapter 3: "Facebook as a Platform for Social Media Marketing" for details) increases the level of engagement over the brand related content created by the company. Since this feature is not available for free, it would be interesting to examine the extent of engagement increase in order to evaluate the value of such investment.

Finally, a study which could explain the relations and mutual influence between different forms of media: paid (e.g., television, newspapers, etc.), owned (e.g., web pages, mobile apps, etc.) and earned media (e.g. word-of-mouth, Facebook, etc.), would contribute into the direction of general understanding of the value of each of these elements of the marketing mix.

10.3.2.2. Generalization over Different Industry Domains

The study presented in this thesis is conducted over brand pages for FMCG products. 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.

The main segment where the differences could appear is in regard to the UGC on these pages and the responses to different content categories offered by the companies. For example, Disney fans probably differ from those of Tiffany & Co., not only in regard to the demographics data, but also in regard to their communication style, motivations for participations and expectations from the

brand they liked in terms of offered content. Thus further investigation in this direction is needed to address this issue.

Finally, an interesting comparison could be made to the pages which are not created by brands, but are created by celebrities instead. These pages also show great success, measured by the number of fans. For example, the singer Lady Gaga has more than 53 million fans on her page, which is even more compared to Coca-Cola as a leading brand on Facebook. Analysis of these pages could provide insights into the communication policies and marketing strategies of these pages and might bring some fresh ideas into the retail domain.

10.3.2.3. Generalization over Different Social Media Platforms

Finally, research conducted in this study is limited on Facebook as a platform for social media marketing. Still, market research shows that other social media platforms are also used by practitioners for engaging into brand related communication. For example, Twitter offers the possibility for creation of channels to which consumers with Twitter profiles can subscribe and follow the conversation related to their favourite brands.

In addition, new social media platforms are constantly emerging, such as Google+ which is approaching Facebook and Twitter very fast in terms of adoption. Thus extending the research presented in this thesis to other existing platforms could provide possibilities to generalize the obtained results or identify specific domains where performance differences appear. This would be particularly important for those companies who are just considering to join social media, in order to select a platform which is most suitable for their needs and goals.

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APPENDICES

Appendix I: High level characteristics of the top Facebook brand pages form the Fast-Moving Consumer Goods Industry

Brand	Fans		Moderator Posts			User Posts		
	N[a]	Growth[b]	N[b]	AVG[c]	Eng. Rate	N[b]	AVG[c]	Eng. Rate
Coca-Cola	36'585'722	10%	13	0.22	0.000187	13696	228.27	0.000000076
Starbucks	26'568'303	8%	25	0.42	0.000841	18834	313.90	0.000000179
Red Bull	25'328'419	7%	92	1.53	0.000250	0	0.00	0.000000000
Oreo	23'734'423	6%	17	0.28	0.000402	2117	35.28	0.000000037
Skittles	19'628'802	7%	57	0.95	0.000410	2677	44.62	0.000000048
Pringles	16'258'916	12%	67	1.12	0.000085	2752	45.87	0.000000024
Monster Energy	12'866'375	14%	142	2.37	0.000204	10372	172.87	0.000000081
McDonald's	12'215'217	40%	1	0.02	0.000777	0	0.00	0.000000000
Nutella	11'917'508	17%	18	0.30	0.000338	0	0.00	0.000000000
Dr Pepper	10'923'342	5%	106	1.77	0.000506	13289	221.48	0.000000323
Taco Bell	7'664'011	8%	85	1.42	0.001029	8139	135.65	0.000000341
Pepsi	6'894'498	11%	98	1.63	0.000521	6365	106.08	0.000000103
Mountain Dew	6'312'189	6%	23	0.38	0.001136	3020	50.33	0.000000351
Buffalo Wild Wings	6'001'986	13%	115	1.92	0.000307	3339	55.65	0.000000064
5 Gum	5'590'471	9%	0	0.00	0.000000	891	14.85	0.000000330
Dunkin' Donuts	5'423'131	9%	93	1.55	0.000474	8733	145.55	0.000000230
Sprite	5'154'844	47%	1	0.02	0.000129	1074	17.90	0.000000232
Pizza Hut	4'969'803	29%	60	1.00	0.000254	4451	74.18	0.000000190
Kit Kat	4'840'509	33%	38	0.63	0.000281	3425	57.08	0.000000090
Chick-fil-A	4'750'804	3%	27	0.45	0.000544	2602	43.37	0.000000173
Dippin' Dots	4'577'831	6%	23	0.38	0.000148	239	3.98	0.000000075

Brand	Fans		Moderator Posts			User Posts		
	N[a]	Growth[b]	N[b]	AVG[c]	Eng. Rate	N[b]	AVG[c]	Eng. Rate
Gatorade	4'399'366	6%	96	1.60	0.000258	904	15.07	0.000000068
Domino's Pizza	4'340'110	27%	112	1.87	0.000577	7043	117.38	0.000000096
Slurpee	4'325'088	6%	0	0.00	0.000000	277	4.62	0.000000219
Dairy Queen	3'815'738	18%	32	0.53	0.000284	1013	16.88	0.000000114
Krispy Kreme Doughnuts	3'801'554	8%	23	0.38	0.000687	0	0.00	0.000000000
Ben & Jerry's	3'483'379	7%	131	2.18	0.000126	1510	25.17	0.000000360
Kellogg’s Pop-Tarts	3'480'495	12%	21	0.35	0.000141	501	8.35	0.000000272
Baskin-Robbins	3'363'546	19%	42	0.70	0.000500	1004	16.73	0.000000264
Kinder Surprise	3'342'607	21%	12	0.20	0.000255	648	10.80	0.000000057
Lay's	3'220'645	17%	13	0.22	0.000227	1366	22.77	0.000000048
Vitaminwater	3'023'714	5%	1	0.02	0.000132	1040	17.33	0.000000407
Twix	3'020'883	26%	27	0.45	0.000532	1226	20.43	0.000000108
Snickers	2'904'408	28%	28	0.47	0.000637	1118	18.63	0.000000099
Arizona Iced Tea	2'712'300	14%	63	1.05	0.000462	671	11.18	0.000000268
M&M's U.S.A.	2'685'728	17%	92	1.53	0.000700	2503	41.72	0.000000248
Life Savers Gummies	2'557'410	19%	37	0.62	0.000255	183	3.05	0.000000111
Kinder Bueno	2'502'956	31%	0	0.00	0.000000	890	14.83	0.000000057
Sour Patch Kids	2'443'625	24%	61	1.02	0.000265	556	9.27	0.000000225
Burger King	2'404'909	79%	79	1.32	0.000532	6577	109.62	0.000000194
Trident® Chewing Gum	2'270'645	18%	4	0.07	0.000029	306	5.10	0.000000558
Frito-Lay	2'194'315	3%	26	0.43	0.000363	872	14.53	0.000000465
Tic Tac	2'176'727	44%	11	0.18	0.000099	382	6.37	0.000000065
Hard Rock	2'125'187	5%	73	1.22	0.000357	1597	26.62	0.000001278
Doritos	2'117'932	56%	22	0.37	0.000309	1705	28.42	0.000000709
Toblerone	2'073'377	19%	17	0.28	0.000357	353	5.88	0.000000490

Brand	Fans		Moderator Posts			User Posts		
	N[a]	Growth[b]	N[b]	AVG[c]	Eng. Rate	N[b]	AVG[c]	Eng. Rate
Cadbury Creme Egg	2'062'032	8%	2	0.03	0.000712	935	15.58	0.000000782
Papa John's Pizza	1'997'206	10%	74	1.23	0.000437	5594	93.23	0.000000529
Cadbury Wispa	1'794'119	2%	61	1.02	0.000488	1038	17.30	0.000000799
ICEE	1'746'202	22%	69	1.15	0.000132	2097	34.95	0.000002005
Tim Hortons	1'720'900	5%	21	0.35	0.001034	2032	33.87	0.000000776
Panda Express	1'688'461	29%	18	0.30	0.000314	910	15.17	0.000000135
Cold Stone Creamery	1'676'449	8%	18	0.30	0.000295	625	10.42	0.000000935
Wendy's	1'640'488	19%	69	1.15	0.000552	1751	29.18	0.000000419
Outback Steakhouse	1'638'200	9%	40	0.67	0.000763	1451	24.18	0.000000301
Hooters	1'612'289	25%	50	0.83	0.001404	2560	42.67	0.000001027
Kool – Aid	1'588'714	16%	22	0.37	0.000474	937	15.62	0.000000886
Bingo!	1'570'112	10%	63	1.05	0.000939	0	0.00	0.000000000
Chipotle Mexican Grill	1'545'461	10%	7	0.12	0.000505	4976	82.93	0.000002569
Fanta	1'522'753	67%	46	0.77	0.000060	1865	31.08	0.000001204
Nespresso	1'428'793	11%	15	0.25	0.001251	1140	19.00	0.000001280
WARHEADS	1'400'633	35%	19	0.32	0.000793	669	11.15	0.000001528
Diet Coke	1'392'726	21%	1	0.02	0.000418	663	11.05	0.000001660
Pillsbury	1'382'356	15%	111	1.85	0.000460	696	11.60	0.000002008
Cadbury Celebrations	1'200'287	15%	243	4.05	0.001907	509	8.48	0.000002689
Little Debbie	1'164'285	10%	45	0.75	0.001092	991	16.52	0.000000354
Jamba Juice	1'154'797	13%	66	1.10	0.000240	0	0.00	0.000000000
Nescafé	1'153'004	20%	22	0.37	0.000326	668	11.13	0.000000534
Butterfinger	1'138'096	19%	38	0.63	0.001088	473	7.88	0.000001165
Rockstar Energy Drink	1'115'195	26%	212	3.53	0.000280	1361	22.68	0.000000540
Cafe Coffee Day	1'086'974	30%	106	1.77	0.001174	1407	23.45	0.000011902

Brand	Fans		Moderator Posts			User Posts		
	N[a]	Growth[b]	N[b]	AVG[c]	Eng. Rate	N[b]	AVG[c]	Eng. Rate
Mentos US	1'070'540	15%	71	1.18	0.000296	525	8.75	0.000001384
Jarritos	1'020'803	8%	30	0.50	0.000618	242	4.03	0.000001653
Lipton Brisk	968'440	12%	82	1.37	0.000426	1862	31.03	0.000002639
Heinz Ketchup	897'602	7%	29	0.48	0.000679	1906	31.77	0.000000697
Carl's Jr.	859'134	12%	48	0.80	0.000520	698	11.63	0.000000842
Ching's Secret	835'513	0%	5	0.08	0.000177	22	0.37	0.000000706
Jones Soda	811'520	10%	80	1.33	0.000067	665	11.08	0.000003856
Wawa	806'744	4%	32	0.53	0.000966	549	9.15	0.000001517
Pepsi Max	804'307	53%	102	1.70	0.000235	621	10.35	0.000000785
Nabisco Cookies	798'932	6%	22	0.37	0.000266	453	7.55	0.000000482
Whole Foods Market	766'403	8%	131	2.18	0.000645	0	0.00	0.000000000
Pepsi Max	758'132	24%	58	0.97	0.000695	125	2.08	0.000001518
Marmite	751'762	4%	80	1.33	0.001426	1599	26.65	0.000003071
Snapple	726'273	31%	105	1.75	0.000574	1322	22.03	0.000001924
Coca-Cola Zero	724'324	12%	4	0.07	0.000029	1054	17.57	0.000002058
Arby's	722'412	18%	55	0.92	0.000700	573	9.55	0.000001460
Tabasco	678'139	6%	20	0.33	0.000842	529	8.82	0.000001548
Nestle Drumstick	676'005	10%	25	0.42	0.000464	107	1.78	0.000002080
Cheetos	664'539	23%	11	0.18	0.000570	482	8.03	0.000000580
DiGiorno	609'775	23%	47	0.78	0.000317	1337	22.28	0.000000545
Florida's Natural	439'450	26%	51	0.85	0.002615	414	6.90	0.000003349
Wheat Thins	423'335	6%	19	0.32	0.000189	468	7.80	0.000001074
Nestlé	286'423	34%	27	0.45	0.000578	1122	18.70	0.000001667
Lipton Iced Tea	238'888	3%	31	0.52	0.000590	357	5.95	0.000008241
Popchips	232'976	7%	33	0.55	0.000657	508	8.47	0.000003547

Brand	Fans		Moderator Posts			User Posts		
	N[a]	Growth[b]	N[b]	AVG[c]	Eng. Rate	N[b]	AVG[c]	Eng. Rate
Tropicana	169'396	12%	60	1.00	0.000620	551	9.18	0.000009630
Sierra Nevada	130'130	6%	28	0.47	0.006174	907	15.12	0.000010290
Campbell's Condensed Soup	49'016	25%	43	0.72	0.003192	290	4.83	0.000053898
PepsiCo	44'089	17%	144	2.40	0.000000	346	5.77	0.000030985
AVERAGE (per page):		17%	50	0.84	0.000592	1952	32.54	0.000001978

a. Obtained on January 1st, 2012
b. For the selected period: from January 1st to March 1st 2012
c. Per day

Appendix II: Descriptive statistics for the engagement over the content created by Facebook brand page moderators

		Enagement Rate	Likes Ratio	Comments Ratio	Shares Ratio
Mean	*Value*	0.000675	0.000122	0.000045	8.976626
	Std. Error	0.000020	0.000004	0.000008	0.159276
95% CI for Mean	*Lower Bound*	0.000635	0.000113	0.000028	8.664376
	Upper Bound	0.000715	0.000130	0.000061	9.288877
5% Trimmed Mean		0.000675	0.000368	0.000071	0.000017
Median		0.000020	0.000242	0.000038	0.000003
Variance		0.000635	0.000001	0.000000	0.000000
Std. Deviation		0.000715	0.000969	0.000308	0.000601
Minimum		0.000498	0.000000	0.000000	0.000000
Maximum		0.000334	0.026227	0.006749	0.041288
Range		0.000002	0.026227	0.006749	0.041288
Interquartile Range		0.001439	0.000399	0.000085	0.000024
Skewness	*Value*	18.020263	8.307810	64.481556	1.925653
	Std. Error	0.034510	0.034510	0.034510	0.034510
Kurtosis	*Value*	582.739142	112.258214	4402.700757	3.728649
	Std. Error	0.069007	0.069007	0.069007	0.069007

Appendix III: Results of the post-hoc analysis for the engagement over the content created by Facebook brand page moderators for the posting hour variable

Posting Hour		LR		CR		SR		ID	
		U	r	U	r	U	r	U	r
0	4	2283.0	0.26**	-	-	-	-	-	-
0	5	**2945.0**	**0.30***	-	-	3088.0	0.29***	-	-
0	6	**2966.0**	**0.45***	-	-	**4315.5**	**0.30***	-	-
0	7	**1345.0**	**0.41***	2179.0	0.24**	2122.5	0.26**	-	-
0	8	**2437.0**	**0.36***	3163.0	0.25**	-	-	-	-
0	9	**3997.0**	**0.31***	**3477.0**	**0.37***	4273.5	0.28***	-	-
0	10	3253.0	0.25**	**2966.0**	**0.30***	-	-	-	-
0	11	2501.0	0.27***	-	-	-	-	-	-
0	13	7101.0	0.26***	-	-	**6158.5**	**0.35***	7304.0	0.25***
0	14	13247.0	0.25***	12775.0	0.27***	-	-	-	-
0	15	-	-	-	-	20611.5	0.25***	-	-
0	16	-	-	28330.5	0.21***	-	-	30842.0	0.16***
0	20	-	-	-	-	-	-	25795.0	0.13**
0	21	-	-	-	-	-	-	35621.0	0.17***
1	4	5421.5	0.25**	-	-	-	-	-	-
1	5	2283.0	0.28***	-	-	2506.0	0.27***	-	-
1	6	**2945.0**	**0.41***	-	-	3088.0	0.27***	-	-
1	7	**2966.0**	**0.39***	-	-	4315.5	0.24**	-	-
1	8	**1345.0**	**0.34***	-	-	-	-	-	-
1	9	2437.0	0.28***	**3163.0**	**0.34***	3795.5	0.26***	-	-
1	10	3997.0	0.24**	3477.0	0.26***	-	-	-	-
1	11	3253.0	0.25**	-	-	-	-	-	-
1	13	7699.0	0.25***	-	-	**6857.0**	**0.32***	8455.0	0.19**

Posting Hour		LR		CR		SR		ID	
		U	r	U	r	U	r	U	r
1	14	14411.0	0.24***	14054.0	0.25***	-	-	-	-
1	15	-	-	-	-	22868.0	0.23***	-	-
1	16	-	-	31336.0	0.19***	-	-	-	-
1	21	-	-	-	-	-	-	40771.0	0.12**
2	4	**1285.0**	**0.33*****	-	-	**1265.0**	**0.35*****	-	-
2	5	**1678.0**	**0.36*****	-	-	**1609.0**	**0.39*****	-	-
2	6	**1710.0**	**0.50*****	-	-	**2134.0**	**0.42*****	-	-
2	7	**756.0**	**0.49*****	-	-	**1038.0**	**0.40*****	-	-
2	8	**1390.0**	**0.42*****	-	-	1948.0	0.28**	-	-
2	9	**2323.0**	**0.35*****	**2453.0**	**0.32*****	**2323.0**	**0.36*****	-	-
2	10	**1860.0**	**0.31*****	-	-	-	-	-	-
2	11	**1470.0**	**0.32*****	-	-	**1521.0**	**0.32*****	-	-
2	12	-	-	-	-	2311.0	0.28**	-	-
2	13	**4087.0**	**0.30*****	-	-	**2994.0**	**0.46*****	4664.0	0.22**
2	14	7666.0	0.26***	-	-	8102.0	0.24***	-	-
2	15	-	-	-	-	10797.0	0.29***	-	-
2	16	-	-	-	-	18844.0	0.14**	-	-
2	17	-	-	-	-	18915.0	0.19***	-	-
2	21	-	-	-	-	-	-	22271.0	0.13**
3	6	**1755.0**	**0.31****	-	-	-	-	-	-
3	7	**798.0**	**0.35****	-	-	-	-	-	-
3	9	-	-	1760.0	0.29**	-	-	-	-
4	18	5054.0	0.20***	-	-	-	-	-	-
4	19	4551.0	0.23***	-	-	5412.0	0.18**	-	-
4	20	4488.0	0.23***	-	-	-	-	-	-

Posting Hour		LR		CR		SR		ID	
		U	r	U	r	U	r	U	r
4	21	7891.0	0.15**	-	-	-	-	-	-
4	22	5005.0	0.20***	-	-	-	-	-	-
4	23	3528.0	0.22**	-	-	-	-	-	-
5	13	-	-	-	-	-	-	**2181.0**	**0.31*****
5	16	-	-	-	-	9733.0	0.16**	9076.0	0.18***
5	17	9869.0	0.18***	-	-	-	-	11095.0	0.13**
5	18	6551.0	0.24***	-	-	7223.0	0.21***	-	-
5	19	5940.0	0.27***	-	-	6765.5	0.23***	-	-
5	20	5858.0	0.27***	7658.0	0.17**	6988.0	0.21***	7920.0	0.15**
5	21	10290.0	0.18***	-	-	10667.0	0.17***	10651.0	0.17***
5	22	6516.0	0.24***	-	-	7592.0	0.18**	-	-
5	23	4599.0	0.26***	-	-	5225.0	0.21**	-	-
6	9	-	-	**1872.0**	**0.34*****	-	-	-	-
6	12	**1684.0**	**0.31****	-	-	-	-	-	-
6	13	3349.0	0.27**	-	-	-	-	-	-
6	14	5803.0	0.27***	-	-	-	-	-	-
6	15	**7504.0**	**0.31*****	-	-	-	-	-	-
6	16	10371.0	0.27***	-	-	14032.5	0.16**	-	-
6	17	**9902.0**	**0.31*****	-	-	-	-	-	-
6	18	**6427.0**	**0.38*****	-	-	10022.5	0.24***	-	-
6	19	**6165.0**	**0.39*****	-	-	9356.5	0.26***	-	-
6	20	**5694.0**	**0.41*****	10779.0	0.18**	9907.5	0.22***	-	-
6	21	**10346.0**	**0.31*****	-	-	14908.0	0.19***	-	-
6	22	**6581.0**	**0.37*****	-	-	10820.5	0.19***	-	-
6	23	**4820.0**	**0.39*****	-	-	7451.0	0.21**	-	-

Posting Hour		LR		CR		SR		ID	
		U	r	U	r	U	r	U	r
7	12	**772.0**	**0.35****	-	-	-	-	-	-
7	14	2677.0	0.25***	-	-	-	-	-	-
7	15	3514.0	0.26***	-	-	-	-	-	-
7	16	4756.0	0.23***	-	-	-	-	-	-
7	17	4507.0	0.25***	-	-	-	-	-	-
7	18	**2923.0**	**0.31*****	-	-	4910.5	0.19***	-	-
7	19	**2687.0**	**0.33*****	4988.0	0.17**	4621.5	0.21***	-	-
7	20	**2598.0**	**0.33*****	4494.0	0.20***	4810.5	0.19**	-	-
7	21	4757.0	0.25***	-	-	7279.0	0.15**	-	-
7	22	**2945.0**	**0.31*****	-	-	-	-	-	-
7	23	**2157.0**	**0.34*****	3308.0	0.21**	-	-	-	-
8	15	6261.0	0.22***	-	-	-	-	-	-
8	16	8481.0	0.19***	-	-	-	-	-	-
8	17	8344.0	0.22***	-	-	-	-	-	-
8	18	5416.0	0.29***	-	-	-	-	-	-
8	19	**5011.0**	**0.30*****	7381.0	0.17**	-	-	-	-
8	20	**4845.0**	**0.31*****	6765.0	0.20***	-	-	-	-
8	21	8737.0	0.22***	-	-	-	-	-	-
8	22	5513.0	0.28***	-	-	-	-	-	-
8	23	**3883.0**	**0.31*****	4979.0	0.21**	-	-	-	-
9	12	-	-	**1446.0**	**0.37*****	-	-	-	-
9	13	-	-	**2817.0**	**0.34*****	-	-	3369.0	0.24**
9	15	-	-	8557.0	0.25***	-	-	-	-
9	16	-	-	13323.0	0.16**	13427.5	0.16**	13938.0	0.13**
9	17	13631.0	0.18***	12666.0	0.21***	-	-	-	-

Posting Hour		LR		CR		SR		ID	
		U	r	U	r	U	r	U	r
9	18	8993.0	0.25***	8734.0	0.26***	10049.5	0.22***	-	-
9	19	8267.0	0.28***	8067.0	0.29***	9500.5	0.23***	-	-
9	20	8080.0	0.28***	**7277.0**	**0.32*** **	9771.5	0.21***	-	-
9	21	14295.0	0.18***	13430.0	0.21***	14822.0	0.18***	16338.0	0.13**
9	22	9014.0	0.25***	8589.5	0.26***	10434.5	0.19***	-	-
9	23	6359.0	0.26***	**5345.0**	**0.34*** **	7232.0	0.20**	-	-
10	17	-	-	10965.5	0.14**	-	-	-	-
10	18	7221.0	0.21***	7475.0	0.19***	-	-	-	-
10	19	6554.0	0.23***	6830.0	0.22***	-	-	-	-
10	20	6422.0	0.24***	6189.0	0.25***	-	-	-	-
10	21	11212.0	0.15**	-	-	-	-	-	-
10	22	7161.0	0.20***	7485.0	0.18**	-	-	-	-
10	23	5028.0	0.22***	4537.0	0.26***	-	-	-	-
11	18	5640.0	0.21***	-	-	-	-	-	-
11	19	5235.0	0.23***	-	-	6247.0	0.18**	-	-
11	20	5049.0	0.24***	-	-	-	-	-	-
11	21	8966.0	0.15**	-	-	-	-	-	-
11	22	5695.0	0.20***	-	-	-	-	-	-
11	23	3996.0	0.22***	-	-	-	-	-	-
12	19	-	-	-	-	9255.5	0.16**	-	-
13	16	-	-	-	-	20306.5	0.21***	-	-
13	17	24279.0	0.16***	-	-	23493.5	0.18***	-	-
13	18	15913.0	0.24***	-	-	14383.5	0.29***	18845.0	0.15**
13	19	14566.0	0.27***	-	-	**13530.5**	**0.32*** **	-	-
13	20	14350.0	0.27***	-	-	14192.5	0.28***	-	-

Posting Hour		LR		CR		SR		ID	
		U	r	U	r	U	r	U	r
13	21	25464.0	0.16***	-	-	21411.0	0.25***	-	-
13	22	16041.0	0.22***	-	-	15506.5	0.25***	-	-
13	23	11150.0	0.24***	-	-	10663.0	0.27***	-	-
14	15	-	-	32236.5	0.16**	-	-	-	-
14	17	45312.5	0.17***	46417.0	0.16***	-	-	-	-
14	18	29683.0	0.26***	31910.5	0.22***	35951.5	0.14**	-	-
14	19	**27088.5**	**0.30*****	29351.5	0.25***	33628.5	0.17***	-	-
14	20	26785.0	0.29***	27157.5	0.28***	-	-	-	-
14	21	47401.0	0.18***	49637.5	0.15***	-	-	-	-
14	22	29945.5	0.24***	31439.0	0.21***	-	-	-	-
14	23	20823.0	0.24***	19766.0	0.27***	-	-	-	-
15	16	-	-	-	-	65927.0	0.17***	-	-
15	17	-	-	-	-	76155.0	0.14***	-	-
15	18	56546.0	0.15***	-	-	48360.0	0.26***	-	-
15	19	51315.5	0.19***	-	-	45600.5	0.28***	-	-
15	20	51278.5	0.18***	53543.0	0.15***	47282.0	0.24***	-	-
15	21	-	-	-	-	71459.0	0.23***	-	-
15	22	-	-	-	-	50999.0	0.20***	-	-
15	23	-	-	-	-	35159.0	0.20***	-	-
16	17	-	-	102961.0	0.12***	-	-	-	-
16	18	73096.0	0.16***	70719.0	0.18***	-	-	78406.0	0.11**
16	19	65911.0	0.21***	65084.0	0.22***	-	-	-	-
16	20	66032.0	0.20***	60301.0	0.25***	-	-	-	-
16	21	-	-	109953.0	0.12***	-	-	-	-
16	22	73023.0	0.14***	70070.0	0.17***	-	-	-	-

Posting Hour		LR		CR		SR		ID	
		U	r	U	r	U	r	U	r
16	23	50240.0	0.14**	43983.0	0.22***	-	-	-	-
17	18	-	-	-	-	85642.0	0.12**	-	-
17	19	79373.0	0.15***	-	-	79773.5	0.16***	-	-
17	20	79768.0	0.13***	79653.0	0.14***	-	-	-	-
18	21	-	-	-	-	-	-	90965.0	0.12**
19	21	87594.0	0.13***	-	-	-	-	90368.0	0.11**
20	21	-	-	85092.5	0.13***	-	-	-	-

* $p < 0.05$, ** $p < 0.005$, *** $p < 0.0001$

Appendix IV: Categorical variables' information for engagement over content created by Facebook brand page moderators

Post Level Information			N	Percent
Factor	Entertainment	Yes	2948	58.6%
		No	2087	41.4%
	Information	Yes	698	13.9%
		No	4337	86.1%
	Community Success	Yes	30	.6%
		No	5005	99.4%
	Vividness and Interactivity	photo (vividness = low, interactivity = low)	2032	40.4%
		status (vividness = no, interactivity = low)	1842	36.6%
		video (vividness = high, interactivity = high)	473	9.4%
		link (vividness = medium, interactivity = high)	688	13.7%
	Page Interactivity	High	4641	92.2%
		Low	394	7.8%
	Frequency	> 2 posts per day	455	9.0%
		2 posts per day	1776	35.3%
		1 post per day	2116	42.0%
		< 1 post per day	688	13.7%
	Workday	Yes	4047	80.4%
		No	988	19.6%
	Page Focus	Brand	3224	64.0%
		Product	1811	36.0%

Appendix V: Categorical variables' information for characteristics of Facebook brand pages

Page Level Information			N	Percent
Factor	Page Interactivity	High	93	93.0%
		Low	7	7.0%
	Frequency	> 2 posts per day	2	2.0%
		2 posts per day	16	16.0%
		1 post per day	38	38.0%
		< 1 post per day	44	44.0%
	Page Focus	Brand	58	58.0%
		Product	42	42.0%

Appendix VI: Descriptive statistics for the engagement over the content created by the moderators and fans on Facebook brand pages on a page level

		Community Size	Engagement Rate (over moderator posts)	Engagement Rate (over fan posts)
Mean	*Value*	4158450.29	0.000592	0.000001978
	Std. Error	634435.09	0.000075	0.000000637
95% CI for Mean	*Lower Bound*	2899593.43	0.000444	0.000000715
	Upper Bound	5417307.14	0.000740	0.000003241
5% Trimmed Mean		3090553.98	0.000487	0.000000901
Median		1937466.00	0.000461	0.000000486
Variance		40250788140090.96	0.000000	0.000000000
Std. Deviation		6344350.88	0.000746	0.000006366
Minimum		47851.50	0.000000	0.000000000
Maximum		38339532.50	0.006174	0.000053898
Range		38291681.00	0.006174	0.000053898
Interquartile Range		3156444.13	0.000431	0.000001391
Skewness	*Value*	3.23	4.987000	6.644000000
	Std. Error	0.24	0.241000	0.241000000
Kurtosis	*Value*	11.55	32.872000	49.154000000
	Std. Error	0.48	0.478000	0.478000000

Appendix VII: Tests of model effects for brand engagement over the content created by Facebook brand page moderators

Source	df	Brand Engagement Likelihood Ratio Chi-Square	Likes Likelihood Ratio Chi-Square	Comments Likelihood Ratio Chi-Square	Shares Likelihood Ratio Chi-Square
(Intercept)	1	5259.157**	5202.420**	10518.388**	16728.284**
Entertainment	1	223.023**	194.227**	312.728**	19.103**
Information	1	21.464**	26.520**	23.887**	0.371
Community Success	1	5.153*	8.101*	0.199	0.141
Vividness & Interactivity	3	229.970**	234.128**	6406.367**	618.680**
Page Interactivity	1	0.907	0.244	28.532**	10.263*
Frequency	3	71.395**	99.090**	47.622**	138.934**
Workday	1	0.025	3.507	22.313**	0.095
Page Focus	1	83.613**	58.706**	21.427**	99.839**
Post Length	1	81.873**	40.744**	257.401**	58.908**

* $p < 0.05$, ** $p < 0.0001$

Appendix VIII: Spearman correlation coefficients matrix for the relation between the engagement, loyalty, word-of-mouth, community size and growth

	Growth Rate	Community Size	Engagement Rate (per moderator post)	Engagement Rate (per fan post)	Fan Posts	Returning Fans (%)	Talking About Rate	Positive Fan Posts (%)	Negative Fan Posts (%)	Neutral Fan Posts (%)
Growth Rate	1.000									
Community Size	0.003	1.000								
Engagement Rate (per moderator post)	-0.078	-0.291**	1.000							
Engagement Rate (per fan post)	-0.036	-0.769**	0.297**	1.000						
Fan Posts (per user)	-0.461**	-0.402**	0.313**	0.573**	1.000					
Returning Fans (%)	0.117	-0.446**	0.250*	0.577**	0.754**	1.000				
Talking About Rate	0.896**	-0.104	0.074	0.084	-0.294**	0.267**	1.000			
Positive Fan Posts (%)	-0.217*	-0.202*	0.047	0.336**	0.210*	0.018	-0.279**	1.000		
Negative Fan Posts (%)	0.030	-0.057	0.151	0.262**	0.372**	0.396**	0.065	-0.108	1.000	
Neutral Fan Posts (%)	0.218*	0.113	-0.210*	-0.003	0.057	0.208*	0.230*	-0.421**	0.007	1.000

* $p < 0.05$, ** $p < 0.01$

Appendix IX: Emoticons and corresponding emotions in user-generated content on Facebook brand pages

Emoticon	Emotion
:) :-) =) x) (:	Joy (smiling)
:D	Excitement
;) ;-) ;D ;P (;	Wink
xD =D ^^ ^.^	Happiness (laughing)
<3 ♥ *_* *.* **	Love
:P	Playfulness (tong out)
:O	Surprise
:S	Skepticism
(Y)	Support (thumbs up)
:(=(	Sadness
-.-	Annoyance

Appendix X: Interjections and corresponding emotions in user-generated content on Facebook brand pages

Interjection	Emotion
Mmm	Pleasure
Hmm	Wondering
Mhmm	Confirmation
yeah, uee, juhu, jipi, wuhu, boah	Excitement
haha, hihi	Laughter
jum jum, njam njam	Tasty
Wow	Surprise

Appendix XI: Example listing of a Post object returned by the Facebook Graph API including Comments and Likes arrays


```
{
   "id": "281678169597_10151044596874598",
   "from": {
      "name": "ok.-",
      "category": "Company",
      "id": "281678169597"
   },
   "message": "Vielen Dank David und Daniel [...]",
   "picture": "http://photos-e.ak.fbcdn.net/ [...]",
   "link": "http://www.facebook.com/photo.php?fbid= [...]",
   "icon": [...]",
   "actions": [
      {
         "name": "Comment",
         "link": [...]"
      },
      {
         "name": "Like",
         "link": [...]"
      }
   ],
   "type": "photo",
   "object_id": "10151044596834598",
   "created_time": "2012-07-18T11:39:10+0000",
   "updated_time": "2012-07-19T07:06:28+0000",
   "likes": {
      "data": [
         {
            "name": "Stefania Misteli",
            "id": "100000877921428"
         },
         [...]
      ],
      "count": 26
   },
   "comments": {
      "data": [
         {
            "id": "281678169597_10151044596874598_7440572",
            "from": {
               "name": "ok.-",
               "id": "281678169597"
            },
            "message": "[...]",
            "created_time": "2012-07-19T06:58:02+0000"
         },
         [...]
      ],
      "count": 11
   }
}
```

CURRICULUM VITAE

Irena Pletikosa Cvijikj

Personal Data

Date of Birth	07.06.1976
Place of Birth	Skopje, Macedonia

Education

12/2009 – 12/2012	**ETH Zurich, Switzerland** Dr. sc. ETH Zürich
12/2003 - 07/2005	**Ss. Cyril and Methodius University, Skopje, Macedonia** MSc in Electrical Engineering
10/1994 - 06/1999	**Ss. Cyril and Methodius University, Skopje, Macedonia** BSc in Electrical Engineering

Professional Experience

12/2009 - present	**ETH Zurich, Switzerland** Research Assistant
08/2002 - 08/2009	**ITS Iskratel, Skopje, Macedonia** Technical Coordinator, Team Leader, Senior SW Engineer
01/2002 - 08/2002	**ITS Iskratel, Skopje, Macedonia** System Engineer
01/2001 - 01/2002	**Siemens AG, Munich, Germany** System Engineer
07/1999 - 01/2001	**MakSystem, Skopje, Macedonia** Software Engineer

Certificates

Stamford Global	Managing Multiple & Complex Projects
Semos Education	Management of Successful Team & Advanced Techniques Project Management
Sun Microsystems	Sun Certified Programmer for the Java 2 Platform 1.4

Certificates

Brainbench	Master Brainbench Certification in HTML 4.0
	Brainbench Certification in CSS 2
	Brainbench Certification in Java 2
Alexandria	CompTIA Linux+
	Fundamentals of Java Programming v1.2
Oracle University	Create Servlets and JavaServer Pages
	Enterprise DBA Part 1A: Architecture and Administration
	SQL for End Users
TManagement Forum	eTOM Distilled & NGOSS Distilled
Siemens Training Center	XpressPass 140/142/144 R4.0 Operation, Administration and Maintenance
	ICDN Interconnecting CISCO Network Devices
	FMX II/CMX System OAM, Siemens Training Center
	MSX 36140/144 R3.0 / 46020 R3.2, Siemens Training Center
	XpressLink OAM V2
	FastLink System OAM
	Technology and Applications of ATM
	Technology, Applications and Internetworking LAN/WAN (Part I & Part II)
	Introduction to Data Networking

Publications

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