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Social Media Research: A Narrative Review

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Markus Kick

I SOCIAL MEDIA RESEARCH: A NARRATIVE REVIEW

Abstract

Even though the technological developments of web 2.0 and social media opened up a multitude of possibilities for companies to communicate with their customers, marketers, to a certain extent, lost direct control of their brands. Users are able to exchange opinions about companies, products, services, or brands independent of corporate influences at high speed and almost no cost. Marketing research has quickly picked up the new technological developments, generating enormous numbers of studies. However, the findings are highly diverse and confusing at the same time. This paper provides a systematic overview of top-tier social media research. A main emphasis is put on empirical studies that investigate the effects of user-generated content on measurable corporate performance indicators. A total of 102 articles are used as input for the conducted qualitative meta-analysis. Findings are sorted along the proposed framework of the “*social media value chain*”. The analysis encompasses effects of electronic word-of-mouth on corporate consumer mindset metrics, product and market performance indicators, and financial performance measures. The analysis extracts the inherent moderators of electronic word-of-mouth-effects and provides a suitable framework for discussion. In addition, the dual role of companies as moderators of ongoing social media communication and content creators within viral marketing campaigns is also dissected. Social media conversations are a powerful force that shows effect along the whole value chain. Pure volume measures show the strongest effect. Even though valence measures contain a high degree of information, inconsistent results can be observed depending on valence operationalization and empirical methods used. Research needs to develop a better and deeper understanding of valence measures. Further, experimental field studies provide a good starting point for future empirical work. The multitude of moderator effects reveals that the impact of electronic word-of-mouth is not generalizable across industries, product categories, and social media platforms. However, social media conversations contain rich information that has to be utilized by the marketing profession.

1 Motivation

Within the last 15 years, the term “Social Media” has undergone a significant change from a simple buzzword to a widely accepted marketing and communication tool (e.g., EYRICH et al., 2008, p. 412, WILSON et al., 2011, p. 25). Emerging from the technological evolutions of Web 2.0, it is now on top of the agenda of business executives (KAPLAN and HAENLEIN, 2010, p. 59). With about 1.5 billion users worldwide, social media forms an essential part of today’s online environment and, therefore, plays a key role for marketing managers (CHUI et al., 2012, p. 1). An immeasurable number of social networks and websites like Facebook, YouTube, Twitter, and a vast amount of discussion forums and blogs have opened up tremendous new possibilities for marketers across all industries to immediately and directly engage with their customer base (JAHN and KUNZ, 2011, pp. 96-97). More and more, companies try to exploit these new opportunities and jump on the social media bandwagon. The opportunities for businesses are quite obvious. Companies can extract precious information directly from their (potential) customers by monitoring forums or discussion boards (HENNIG-THURAU and WALSH, 2004, p. 66). They can use social media channels for viral marketing activities (DE BRUYN and LILIEN, 2008, p. 151, HO and DEMPSEY, 2010, p. 1000) and implement crowdsourcing competitions or platforms for customers and brand evangelists to bond them to the brand they admire (PATTERSON, 2012, p. 527). Moreover, firms can implement social media as interactive and individual communication tool in service environments to foster relationship marketing (THORBJØRNSSEN et al., 2002, p. 17). Marketing managers face the challenge to integrate social media into their existing strategies to remain competitive in today’s market. Consequently, marketing budgets are shifted more and more towards the social media sector. The “CMO Survey” from Duke University and the American Marketing Association shows a peak in social media marketing expenses in 2014 with 7.4% of total marketing budgets. A predicted increase in spending of up to 18.1% within the next five years confirms the ongoing change of mind (CMOSURVEY, 2014, p. 25).

Social Media has drastically changed the marketing game. Rather than pushing a brand’s message at its consumers, brands have to involve consumers into an ongoing dialogue (HENNIG-THURAU et al., 2010, p. 313). Social media allows consumers to directly and immediately engage in the process by producing, distributing, and consuming information in real time. Social media-based conversations occurring between consumers are outside managers’ direct control (MANGOLD and FAULDS, 2009, p. 357) and the flow of information about brands, products, services, and companies has become multidirectional, interconnected, and difficult to predict

(HENNIG-THURAU et al., 2010, p. 313). This new balance of power allows less influential stakeholder groups to share their positions, needs, or thoughts in a public, almost real-time, and highly visible way. Consequently, marketers in those peer-to-peer environments have become an intruder, more talked-about than actually talking (DEIGHTON and KORNFELD, 2009, p. 4). Consumer product reviews, product ratings, recommendations, status updates, blog posts, or discussion board conversations are just some examples that all play into the multifaceted and complex term of social media (LEE et al., 2008, p. 341). They are all pre-purchase information sources that are available 24/7, show influence on people's buying behavior, and, therefore, a firm's sales (GU et al., 2011, p. 182). Even though social media is omnipresent and its importance unquestioned, many executives are still hesitant and uncertain about this new form of media, because they do not completely understand the various forms it can take, the different consequences it may have, and how to engage with it and learn (KIETZMANN et al., 2011, p. 241).

Not surprisingly, social media has attracted scholarly attention from diverse disciplines within the last decade. The internet's accessibility, reach, and transparency, as well as the almost unlimited access to archived consumer interactions have provided research with valuable data resources (KOZINETS et al., 2010). Especially marketing scholars provided a multitude of studies that investigate different effects of the new social media phenomenon. Reasoned within the works about traditional word-of-mouth, effects of online consumer interactions could be shown on consumer mindset metrics (e.g., NAMBISAN and WATT, 2011), market performance indicators (e.g., CHEVALIER and MAYZLIN, 2006), and even stock market movements (e.g., ANTWEILER and FRANK, 2004). However, literature states that published studies on the effectiveness of electronic word-of-mouth and social media are fragmented, use a multitude of different research approaches, and lack a conclusive overall picture of the current state-of-the-art (CHEUNG and THADANI, 2012). Research calls for integrative works that provide a more generalizable picture (LABRECQUE et al., 2013) and systematically identifies the current challenges (GENSLER et al., 2013).

It is necessary to step back, synthesize research outcomes, and identify flaws within the current research landscape. The background of losing direct control of brands and the constellation of nearly unfiltered information transfer within a web 2.0 environment, exhibits the necessity for companies to understand the underlying processes of how social media might impact one's business. Companies strive to know how to appropriately counteract negative developments and how to take advantage of social media communications. Therefore, the need for an overall

picture, rather than compartmentalized partial aspects, becomes obvious. To the best of my knowledge, there is no study that offers an aggregation of high quality research within social media with a focus on the effects on measurable corporate performance indicators. The objective of this paper is twofold. First, I summarize and aggregate research outcomes along the social media value chain inspired by the framework of KELLER and LEHMANN (2003, p. 29). Second, I derive implications for research by identifying research gaps for further investigation and give advice for practitioners how to beneficially use social media.

In the following, I derive an operational definition of social media for the paper at hand and shed light onto the complex phenomenon. In addition, I lay stress on the necessity for consolidation within the research stream, the contribution of my work, and introduce the social media value chain as an efficient framework for this study's purposes. After the introduction to the methodology, I present the results of the analysis. I subsequently conclude this paper with an evaluation of results, derive final implications for practitioners, and identify promising avenues for further research.

2 Conceptual Framework

2.1 Word-of-Mouth in an Interactive Environment

The information exchange on social media platforms about companies and their products and services has been given different names like “*user generated content*” (UGC)¹, “*voice of the consumer*”, “*chatter*”, or simply “*buzz*” (GODES and MAYZLIN, 2004, CABLE et al., 2000, LIBAI et al., 2009, TIRUNILLAI and TELLIS, 2012). But what exactly is meant by those terms on the different channels like blogs, Facebook, Twitter, or discussion boards? The bottom line of all information exchange on social media platforms comes back to a “[...] *person-to-person communication between a perceived non-commercial communicator and a receiver concerning a brand, a product, or a service offered for sale*” (ARNDT, 1967, p. 190), the basic definition of word-of-mouth (WOM). As a key factor, WOM communication is independent from any commercial influences and mostly takes place after a certain purchase, service, or product experience. WOM, as commercially unbiased, shows a high credibility and is even more effective than traditional marketing tools (BICKART and SCHINDLER, 2001, p. 36, ENGEL et al., 1969, p. 4, KATZ and LAZARFELD, 1955, p. 44). Whereas ARNDT (1967, p. 190) was defining WOM as an oral person-to-person communication process between two individuals, the definition was further shaped and adapted to new situations. Research expanded the view to a group phenomenon (BONE, 1992, p. 579) and scholars also included other communication types than face-to-face into the definition (BROWN et al., 2005, p. 125). After the developments of Web 2.0, “*electronic Word-of-Mouth*” (eWOM), 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., 2004a, p. 39), became ubiquitous and an even more powerful tool than traditional WOM of today’s society (e.g., CLEMONS, 2009a, p. 15, GODES and MAYZLIN, 2004, p. 545).

A fundamental aspect of both WOM and eWOM is that they mostly result of a previous product or service experience. It is typically not biased by the desire for a sale which, at the same time, does not imply a disregard of a sender’s motivations behind the WOM messages for recipients (GODES et al., 2005, p. 418). Research developed different views on the antecedents of WOM activities. In their meta-analysis, MATOS and ROSSI (2008, pp. 579-582) sum up the diverse

¹ Please note that UGC is a broad term for social online communication. Videos on YouTube, knowledge contributions to Wikipedia, or pictures on Flickr are examples for UGC that does not necessarily have to be about products, services, or brands. As this paper strives to investigate effects of social media along the value chain, I understand the term UGC as online information exchange on social media platforms that talks about companies, their products, services, or brands.

landscape and identify the most investigated antecedents. They discover a high satisfaction with products and services, a high loyalty with a company or brand, a high quality of products and services, a high commitment, a high level of trust, and an elevated level of perceived value as the main drivers for positive word-of-mouth (pWOM) creation and vice versa for negative word-of-mouth (nWOM). SUNDARAM et al. (1983, p. 530) find that satisfying employee-consumer contact experiences are one of the main drivers of pWOM and BROWN et al. (2005) add that consumers' identification with a company or brand also enhances WOM contributions. From a more psychological angle, BERGER and SCHWARTZ (2011, p. 870) state the importance of motivations (e.g., self-presentation) for WOM contributions, because consumers do not only communicate product related information, but also partly reveal their personalities. The antecedents mentioned above are mostly derived from traditional WOM settings but can also be seen as valid frameworks for eWOM communications (GRUEN et al., 2006, p. 450). For this reason, the next paragraphs will show general similarities and key differences between the two notions.

The majority of scholars see WOM and eWOM communications as quite similar and closely related concepts. HENNIG-THURAU et al. (2004a, p. 40) showed that contributors within eWOM communications exhibit a similar set of motivations as traditional WOM participants. Prior research also showed that nWOM has a higher persuasiveness than pWOM in offline (e.g., AHLUWALIA, 2002, p. 271) and online settings (e.g., SEN and LERMAN, 2007, p. 90). The high influence on people's purchase intention could also be shown in both situations (e.g., PARK et al., 2007, p. 136, EAST et al., 2008, p. 215). Even though the face-to-face aspect of traditional WOM was partially lost, eWOM still shows higher credibility and higher influence on people's choice behavior than traditional marketing and advertising measures (GODES and MAYZLIN, 2004, p. 545, TRUSOV et al., 2009, p. 90, SENEAL and NANTEL, 2004, p. 167), even though the majority of WOM communications with 76% still occur face-to-face (KELLER and LIBAI, 2009, p. 5).

While WOM and eWOM communications have much in common, there are also key differences. Internet users now have global access to archived consumer articulations and are able to reach far beyond the local community (CHEN and XIE, 2008, p. 479). At almost no cost, internet users can post reviews in real time (DELLAROCAS, 2003, p. 1407). Consumers receive and are influenced by information and evaluations about products, services, and also companies not only from people they personally know, but from a myriad of totally unrelated participants (HENNIG-THURAU and WALSH, 2004, p. 51). Within the traditional WOM setting, people

interact with strong and weak ties (BROWN and REINGEN, 1987, p. 350). In contrast, the online environment leads to mostly anonymous communications based on weak tie relationships (SMITH et al., 2005, p. 20). However, eWOM still can be seen as a trustworthy and commercially unbiased source of information that helps consumers to manage product variety, handle market complexity, and reduce inherent uncertainty in the complex online environment (PATHAK et al., 2010, p. 166, PARK and LEE, 2009, p. 62). Taking into account that 60% of all online purchases are directly influenced by eWOM and UGC², justifies the high attention given by practitioners and academics (FREEDMAN, 2011, p. 9, WINER, 2009, pp. 110-111).

As data access for traditional WOM research has always been limited to an offline setting, the developments of web 2.0 not only strengthened the role of the consumer, but also opened up possibilities for academics and practitioners to access a tremendous amount of data by simply reading the internet (GODES and MAYZLIN, 2004, p. 558). They now can learn from conversations on the internet and even use the unbiased UGC information as inexpensive market research tool to measure the current temperature of their products and brands (KOZINETS et al., 2010, p. 71, DROGE et al., 2010, p. 79). Scholars now bring the insights from traditional WOM back to life in an online environment of large-scale data access (OINAS-KUKKONEN et al., 2010, p. 62). Thus, a boost in (e)WOM literature from 829 articles before the year 2000 to 3,877 after the introduction of web 2.0 can be recorded³.

Scholars approach the eWOM phenomenon from many different angles. Literature mentions two important research streams (AGARWAL et al., 2008, p. 244, IRIBERRI and LEROY, 2009, p. 6, OINAS-KUKKONEN et al., 2010, pp. 62-63). First, the field of computer sciences and information systems research focuses on the technical backgrounds behind the social media environment. Scholars try to answer questions of how to program, design, and implement social media platforms or other social media tools in a way that enhances utility for customers and corporations and investigate consumer interactions with these tools (e.g., WANG and BENBASAT, 2008, KANE and ALAVI, 2008, MA and AGARWAL, 2007). Second, researchers from social and organizational sciences emphasize the social dynamics and individual personality traits and attitudes in the social media world to explain participation and behavior in these interactive environments (e.g., CHEN et al., 2010, WEISS et al., 2008, YUN et al., 2008, SCHAU and GILLY, 2003).

² Due to the restrictions made to the term UGC, eWOM and UGC shall be used as synonyms.

³ To generate these numbers, a keyword search was carried out in the EBSCO databases with the general search term “(electronic) word-of-mouth”, its abbreviations and spellings.

Even though both research streams form a major area of the scientific landscape, this paper wants to change perspective and shift the focus onto studies that take eWOM as an exogenous basis and investigate its influence on corporate performance indicators and preceding marketing metrics. Works with this focus can be categorized in market-level and individual-level analyses (LEE and LEE, 2009, p. 302). Whereas market-level studies mostly rely on large scale datasets extracted from the internet or social media platforms, individual-level studies see eWOM as a process of personal influence, in which communications between two individuals can change the receiver's attitude towards a brand or influence the purchasing decision (CHEUNG and THADANI, 2012, p. 461). Market-level studies try to find effects of eWOM on dependent variables aggregated on company or industry level, whereas individual-level studies focus on how eWOM exposure influences each individual. They both investigate effects of eWOM on corporate performance measures and contribute to the discussion raised in this paper.

To this date, only a few systematic reviews of eWOM research have been published. To the best of my knowledge, there are only three major contributions to the field. First, HENNIG-THURAU et al. (2010) introduce a pinball framework for the illustration of the highly complex social media landscape. In their review, they focus on the impact of new media on customer relationships and, furthermore, also include IT technologies like search and shopping bots, or automated recommendation systems into their analysis. A pinball-like framework with over ten bilateral and dynamic interconnections makes it less suitable for a practical implementation. Unfortunately, the authors do not provide any evidence about how papers have been selected for their study. Thus, it remains questionable how this necessary work has been done in advance of the framework development. Second, GENSLER et al. (2013) take over a brand management perspective. They emphasize the active part of companies in the social media environment through moderating and creating brand stories that can shape consumer' perceptions. However, they do not entirely discuss brand and company related outcomes of online consumer interactions. Further, GENSLER et al. (2013, p. 252) explicitly state that further research should focus on the "[i]mpact of consumer-generated brand stories on brand performance" which argues in favor of the work at hand. Third, CHEUNG and THADANI (2012) apply a classical transmitter-receiver model from social communication literature and add the concepts of stimulus and response. Within their framework, they include effects of eWOM as exogenous and endogenous concepts. This leads to an inconclusive overview of today's research. Furthermore, they see the stimulus (i.e., the communicated message content) as independent from the communicator, which remains doubtful. Moreover, their framework ends at the

response level of purchase intention which falls short when aggregating results especially from market-level studies.

The need for a systematic overview of eWOM research is evident based on the high complexity of interrelationships and potential moderators. A lack of comprehensive review work fuels this opaque landscape and practitioner's hesitation to engage in social media. This paper wants to close this gap and provides a systematic, comprehensive, and qualitative review of main effects of eWOM on corporate performance variables. To provide this narrative review with a solid framework, the concept of the "*brand value chain*" shall be utilized and modified to systematize the large quantity of empirical and theoretical evidence.

2.2 The Social Media Value Chain

With the introduction of the brand value chain, KELLER and LEHMANN offered a holistic and integrated approach to understand the value created by brands. As one of the most valuable company assets, it is important to create, develop, and manage a brand to maximize its "brand equity" to the firm (KELLER and LEHMANN, 2003, p. 27). In addition, the marketing profession is constantly challenged to assess and to declare the value created by their actions on shareholder value (SRINIVASAN and HANSENS, 2009, p. 293). For branding and marketing research it is essential to develop a comprehensive view of how marketing activities lead to brand equity, how it operates, and what causal effect chains can be observed (KELLER and LEHMANN, 2006, p. 753). The brand value chain in the offline environment of marketing assumes that companies are solely in charge of their marketing communication activities. They induce *marketing actions* to influence *perceptual measures* of consumers. These consumer mindset metrics should act as precursor to observable, *behavioral outcomes* that lead to a superior product and market performance and a superior *financial performance* respectively. Thus, the concept of the brand value chain shows how marketing activities create value (GUPTA and ZEITHAML, 2006, pp. 718-719, AMBLER et al., 2002, pp. 14-15). KELLER and LEHMANN (2006, pp. 753-754) further state that it can be seen as a journey from *what companies do* to *what customers think and feel*. The consumer mindset metrics consist of the "Five As" (i.e., awareness, associations, attitude, attachment, and activity) and should trigger sales as the outcome of *what customers do* (i.e., product and market performance). In the last step, these consumer actions are reflected in financial performance measures and show *how the financial markets react*. The value chain can be seen as fairly simple (i.e., it has only four main components). However, feedback effects on previous stages quickly increase the models

complexity (KELLER and LEHMANN, 2006, p. 754). In this paper, I focus on the main effects along the value chain and disregard the inherent problem of endogeneity of the different stages.

SRINIVASAN et al. (2010, p. 674) and KELLER and LEHMANN (2006, p. 754) start the brand value chain journey from “*what marketers do*” by considering the typical marketing mix elements for their framework. However, within the web 2.0 environment it is a new ballgame. Naturally, eWOM does not refer to what marketers or companies do anymore. It rather refers to the question of *what customers do and how they talk about the brand, product, or service*. Even though eWOM takes place next to traditional advertising and marketing actions, it demands a new framework. In Figure 1 I suggest a social media value chain that reflects the structure of chapter 4.

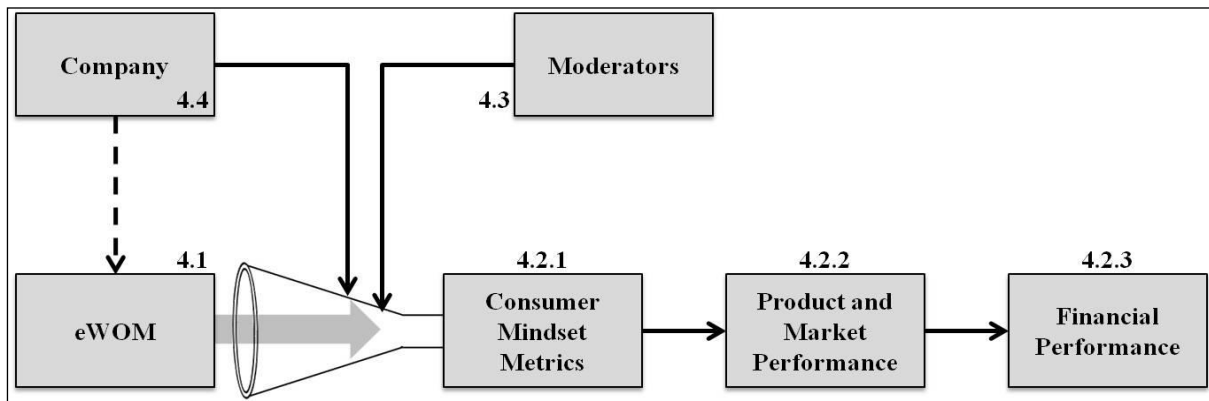


Figure 1: Social Media Value Chain

The operationalization of eWOM with its different measures and variables is discussed in chapter 4.1 and tackles the question of how to measure “*what customers do*” in the social web. In chapter 4.2, the main effects along the value chain are presented before I focus on the moderator effects of those relationships in chapter 4.3. GODES et al. (2005, p. 416) state that companies are moderator, mediator, observer, and participant in the eWOM environment. Thus, there is a constant level of independent buzz about a firm and its products and services that is outside a company’s direct reach. For this reason, I propose a dual role of corporations. First, firms can partly stimulate eWOM discussions by targeted viral marketing campaigns (cf. dashed line in Figure 1). Second, they act as a moderator of the constant noise about their brand and products by moderating ongoing discussions through an active participation in social media conversations. These roles of a company are discussed in chapter 4.4.

3 Literature Review

Literature Research

To compile and systematize the relevant literature in the broad field of social media, procedures suggested by WEBSTER and WATSON (2002), ROSENTHAL (1995), and FARLEY et al. (2004) are closely followed. To identify the relevant works in the area of business studies, a general keyword search was carried out within the three databases of EBSCO, JSTOR, and ELSEVIER. Even though this paper looks at the emerging research stream of social media from a brand and marketing perspective, eWOM and UGC are still multifaceted concepts that can be looked at from many perspectives that are relevant for this study's purpose. Therefore, the database search focused on all journals that are ranked within VHB JOURQUAL 2.1⁴ with a "B" or better to assure quality standards of publications (HENNIG-THURAU et al., 2004b, p. 521). This resulted in 258 target journals for the review at hand from all relevant areas of the business and economic sector. Publications up to the year 2013 have been considered. Subsequently, issue-by-issue research was conducted within the major journals to assure that no important contributions have been missed (FARLEY et al., 2004, p. 148). After the most important contributions have been identified, I went iteratively through their citations to identify relevant prior work. As a last step, conference proceedings and current working papers were identified that can be seen as reflections of the status quo and a real time picture of current research attempts (ROSENTHAL, 1995, p. 184) and partly solve the problem of an inherent "publication bias" (FARLEY et al., 2004, p. 148). Because these unpublished works did not go through journal-peer-review processes, I only included working papers and conference proceedings from well known authors that already published social media research in high quality journals. The existing literature formed the baseline for creating a list of keywords. Important notions were extracted from highly-cited major contributions to the field of social media. To solve the problem that many authors apply different notions for key concepts within social media, I extended the keyword list to abbreviation, spellings, and synonyms for the key concepts (cf. FRANKE, 2001, p. 194). The list was dynamically updated after important contributions with new keywords were identified.

⁴ The complete list of all journals ranked within VHB JOURQUAL 2.1 can be found on http://vhbonline.org/uploads/media/Ranking_Gesamt_2.1.pdf.

Keywords	social(-)media, social(-)network(s), online, (online) communities, (e)WOM, electronic word-of-mouth, online word-of-mouth, word(-)of(-)mouth, (online) recommendations, blog(s), YouTube, Facebook, Twitter, net promoter, chatter, buzz, noise, user generated content, UGC, web 2.0, forum(s), discussion board(s)
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Table 1: Keywords of Literature Search

The issue by issue research was conducted within the journals with the most hits after the keyword search to ensure that no relevant articles of important periodicals have been missed.

A+	Journal of Marketing, Journal of Marketing Research, Marketing Science
A	International Journal of Research in Marketing, Journal of Management Information Systems, MIS Quarterly
B	Journal of Business Research, Journal of Interactive Marketing, International Journal of Electronic Commerce

Table 2: Journals of Issue-by-Issue Search

A total of 374 articles could be identified after all literature-gathering stages. 88 papers in journals ranked as “A+”, 92 in “A” journals, 184 in “B” journals, four conference papers, and six working papers.

Methodological deliberations

Within the literature on meta-analyses, two major types of meta-analysis techniques can be identified. Quantitative studies try to statistically investigate a general effect through an aggregation of empirical results from a relevant set of publications (cf. e.g., HALL and ROSENTHAL, 1995, p. 395, BIJMOLT and PIETERS, 2001, pp. 157-158). This, however, is only possible, when a substantial amount of publications show similar characteristics regarding their empirical methods, study designs, or sampling methods (LIPSEY and WILSON, 2001, pp. 16-23). As outlined in the previous chapters, there is a high methodological and empirical diversity in the current social media research landscape making a quantitative approach inapplicable. Rather, a qualitative meta-analysis in form of a narrative review shall be conducted to compare and combine research results within the eWOM and UGC sector and generate a common framework of understanding (HALL and ROSENTHAL, 1995, p. 396).

Systematization

By screening the abstract and result section of each of the 374 papers identified through the literature compilation stage, I assigned tags to all articles with regard to their topics and variables of interest. After a list of more than 300 tags was created, the catalog was compressed via content-analysis. The so created research clusters were examined regarding their suitability

for this study's purpose to identify works that treat eWOM as an exogenous factor and discuss the influences on corporate performance indicators along the introduced social media value chain. A total of 272 articles were sorted because they did not show a direct link to the eWOM or corporate outcome perspective along the brand value chain (e.g., focus on traditional WOM, editorial articles, etc.). The resulting 102 articles were aligned in consonance with the value chain regarding their dependent variable (cf. Figure 1)⁵. 30 articles were found to investigate effects on consumer mindset metrics, 29 were assigned to product and market performance, and 15 papers focused on eWOM effects on financial performance measures. The role of the company was discussed in 28 articles.

4 Analysis and Results

4.1 Operationalization and Measures of eWOM

When investigating the phenomenon of eWOM, one of the first thoughts goes to the obvious question of how many conversations about a company, brand, product, or service can be found online. The concept of “*volume*” is used in the vast majority of the studies as a starting point for their investigations. *Volume* shows a positive influence across all dependent variables along the value chain. PARK et al. (2007) show that a higher eWOM *volume* has a positive effect on recipients' consumer mindset. Within their experimental setup, they use artificially created consumer reviews as treatment to verify the positive influence on purchasing intentions of a multimedia player. The segment of studies focusing on eWOM effects on product and market performance indicators note a positive link between eWOM *volume* and subsequent online and offline sales, higher early sales, or box office revenues (e.g., DELLAROCAS et al., 2007, GODES and MAYZLIN, 2004, LIU, 2006). *Volume* also forms one of the key measures regarding the effects of eWOM on financial performance metrics. ANTWEILER and FRANK (2004), MCALISTER et al. (2011), or TIRUNILLAI and TELLIS (2012) are just exemplary works that use the *volume* of eWOM about stocks and general eWOM *volume* to predict subsequent trading volume, stock volatility, and stock return. However, the ways in which *volume* numbers are extracted from the different sources on the internet are diverse. The question of how much eWOM can be found on the internet is tackled by extracting eWOM messages with computer based web scrapers, crawlers or scripts with predefined keywords (e.g., SHIN et al., 2011, BERGER and MILKMAN, 2012). Other studies try to gather UGC *volume* by simply looking at

⁵ Appendices 1 – 4 provide detailed excerpts of the identified literature along the social media value chain. The studies assigned to each appendix are arranged in alphabetical order.

the pure numbers of e.g., consumer reviews on Amazon or similar platforms (e.g., CHEVALIER and MAYZLIN, 2006, GODES and MAYZLIN, 2004). Although the methods of accessing *volume* data differ across the identified literature, eWOM *volume* remains one of the strongest and most significant predictors of brand value outcomes (TIRUNILLAI and TELLIS, 2012, p. 198, DUAN et al., 2008b, p. 235). The information inherent in *volume* measures basically answers the question of how much eWOM is out there. The more conversations can be found, the more people will become informed about a specific company, brand, product, or service (GODES and MAYZLIN, 2004, p. 548). But without assessing what consumers actually talk about, the use of a *volume* variable is restricted for practitioners and academics. Consequently, SONNIER et al. (2011, p. 713) state that measuring pure *volume* masks the real effects of eWOM on dependent variables like e.g., sales. The need for a more differentiated measure with a higher degree of information to comprehensibly assess the construct of eWOM and its effects became obvious.

Research quickly drew from traditional theories about WOM and transferred the existing concept of *valence* on the social media landscape. In contrast to *volume* as a simple “count” approach, posts are now assigned with meaning based on the words, language, or tonality used. Within the literature at hand, many different approaches are assigned with the label *valence*. Mostly divided into positive, neutral, and negative postings, it has gained high attention in the research sector due to putting weight on the mostly undifferentiated effects of pure *volume* measures. Along the social media value chain, there are contrary results about the multifaceted construct of eWOM *valence*. Especially within large scale empirical datasets, studies report inconsistent results. Table 3 provides an overview of the different *valence* measures applied in social media research.

<i>Valence Measure</i>	<i>Description</i>	<i>Exemplary Studies</i>	<i>Main Results</i>
<i>Ratings</i>	Consumer generated categorical product ratings (e.g., Amazon 5-star rating scale) are extracted and used as proxy of eWOM valence	CHINTAGUNTA et al. (2010); TIRUNILLAI and TELLIS (2012); DUAN et al. (2008a); ETZION and AWAD (2007); ANDERSON and MAGRUDER (2012)	Positive effect on sales No effect on stock returns No effect on sales Positive effect on online and offline sales
<i>Hand-Coded</i>	Consumer generated posts like product reviews or postings, manually coded regarding their tonality (positive/negative/neutral)	GODES and MAYZLIN (2004); ADJEI et al. (2009); LIU (2006)	No effect on sales Positive effect on purchase behavior No effect on offline sales
<i>IT-Coded⁶</i>	Consumer generated posts like product reviews or message board postings, automatically valence-coded by means of e.g., language processing algorithms	MCALISTER et al. (2011); SHIN et al. (2011); SONNIER et al. (2011)	No effect on stock return Positive effect on market prices Positive effect on sales
<i>Ratios</i>	Based on the valence measures above, the ratio of pWOM/nWOM is calculated	COOK and LU (2009); OH and LIU SHENG (2011)	Positive effect on stock return Positive effect on stock return
<i>Dispersion /Variance</i>	The diversity or dispersion of consumer ratings (e.g., Amazon 5-star scale) is calculated and transferred into measures of disagreement or variance of eWOM	ANTWEILER and FRANK (2004); DAS and CHEN (2007); ZHU and ZHANG (2010); JIMÉNEZ and MENDOZA (2013); SUN (2012)	Negative effect on trading volume No effect on stock variables Negative effect on sales Negative effect on purchase intention

Table 3: Overview of Different Valence Measures

The versatile and partly contradictory effects reported along the social media value chain make it hard to extract a common best practice for the operationalization of *valence*. Research ascribes the stark differences within and across the results of the single *valence* measures mostly to miscellaneous methods applied, industries investigated, or product types looked at (cf. ZHU and ZHANG, 2010, p. 145, DUAN et al., 2008a, p. 1008). However, to the best of my knowledge, no single study investigates the relationships between the different *valence* measures. Whereas the relation and similarity of the hand- and IT-coded *valence* can be calculated statistically, this evidence and knowledge does not exist for the other measures. As ratings are the most applied proxy of eWOM in large scale empirical datasets and are easy to access at almost no cost, it is key for research to investigate questions like: How do star ratings relate to other *valence* measures like written consumer reviews? What makes a positive review a four- or five-star review? Is a three-star review perceived as neutral? What customer articulations lead to one or two star ratings? Answering these questions would help to achieve a better understanding of

⁶ DAS and CHEN (2007, p. 1377) provide a detailed overview of different “valence classifiers” for sentiment extraction of eWOM data collected by web-scrapers programs (i.e., naive-, adjective-, vector distance-, Bayesian-, and discriminant classifier).

the underlying interrelationships and would help to see the overall picture of *valence* measures. Taking a closer look at studies that demonstrate significant influences, it has to be noted that even though the results presented in Table 3 are jagged, there are methodologically accurate studies throughout all stages that show significant effects of eWOM *valence* (e.g., DELLAROCAS et al., 2007, CHAKRAVARTY et al., 2010, OH and LIU SHENG, 2011). Consistent with traditional WOM, the magnitude of nWOM effects is larger than the magnitude of pWOM effects⁷ along the whole social media value chain (e.g., CHEN et al., 2011b, SONNIER et al., 2011, TIRUNILLAI and TELLIS, 2012). Although literature is ambiguous regarding the effects of *valence*, the reasons for its importance is pretty straight forward. PWOM enhances consumers' expectations about product quality, while nWOM reduces it. *Valence* can, thus, be seen as the persuasiveness-factor of eWOM on consumers' attitude (LIU, 2006, p. 76) and its variance as a measure of agreement/disagreement among reviewers or users generating content (JIMÉNEZ and MENDOZA, 2013).

Next to valence and volume, there are also other variables that are applied to investigate eWOM effects along the value chain. The *length* of consumer reviews is regressed by ADJEI et al. (2009) on customers' purchasing behavior. CHEVALIER and MAYZLIN (2006) also examine the effects of the number of words to explain effects on online sales ranks. Both studies do not report any significant influence onto their dependent variables. Another important variable to operationalize eWOM is the concept of *visibility* defined as: "[...] the extent to which product-related conversations are taking place across a broad range of communities" (GODES and MAYZLIN, 2004, p. 546)⁸. In line with the work of HU et al. (2011), they find that visibility has a high influence on people's product judgments and a firm's value respectively. The *visibility* of eWOM is even seen as a stronger predictor than pure volume measures (GODES and MAYZLIN, 2004, p. 559). However, empirical results are too scarce to speak of an overall and generalizable effect.

⁷ In the following, the higher magnitude of nWOM effects compared to pWOM effects will be referred to as the "negativity bias" (e.g., AHLUWALIA, 2002, p. 270). NWOM information, therefore, is more persuasive than comparable positive product ratings, reviews, or evaluations (e.g., ZHANG et al., 2010, p. 1336).

⁸ Note that GODES and MAYZLIN (2004, p. 546) introduce the concept of visibility under the term "dispersion". As dispersion, is referring to a variance in judgments (cf. LUO et al., 2013a, p. 399), I use the term *visibility* for the eWOM distribution across different social media channels.

4.2 Main Effects along the Value Chain

4.2.1 EWOM and the Consumer Mindset

Research on effects of eWOM on consumer mindset metrics fits into the tradition of brand equity literature. Mindset metrics act as an early warning system that indicates not only the effect of specific advertising campaigns, but also that of the entire marketing mix and strategy. Furthermore, mindset metrics are also the building blocks of the hierarchy-of-effects model of advertising. They mostly assume that any marketing stimuli moves the consumer through a hierarchical sequence of events that include cognitions, affection, and result in behavior (SRINIVASAN et al., 2010, p. 673). Even though the marketing profession is always struggling with the fact that marketing actions may not translate into numerable results immediately, the measurement of mindset-metrics on a regular basis can evaluate if marketing is moving customers into the intended direction (KELLER and LEHMANN, 2006, p. 740). As KELLER and LEHMANN (2006, p. 754) add, mindset metrics are not only influenced by a company's actions, but also by personal experience and experiences made by others. Therefore, consumer mindset metrics form an ideal base for the investigation of eWOM effects. Throughout the literature, many hierarchical models have been developed to arrange mindset metrics in an appropriate way to easily follow the process from consumers' first marketing touch-point to the actual purchasing act (VAKRATSAS and AMBLER, 1999, p. 27). Many of them are referred to as "*brand funnel*" or "*purchase funnel*". These causal effect chains in the consumer mindset mostly start with *awareness* measures that subsequently trigger a change in people's *familiarity* with the brand and foster their *attitude* towards the brand. Following, people start to put a brand on their shortlist and *consider* the specific products or services in a pre-purchase stage. This manifests in the actual *purchase decision* and, if repeated, in *loyal* customer behavior (BRIGGS et al., 2005, p. 85). The articles identified in this section are presented in Table 4 and sorted regarding their dependent variable. I follow the logic of KELLER and LEHMANN (2006, p. 745) to sort the articles in a hierarchical order from simple *awareness* aspects as the lowest level within consumer mindset metrics, to *loyalty and satisfaction* as the highest level of post-purchase measures⁹.

⁹ Please note that not all studies are in line with treating purchase decision, satisfaction, or loyalty as consumer mindset metric. For example MUNOZ and KUMAR (2004, p. 383) argue that purchase decision, satisfaction, and loyalty already reflect how customers act and, therefore, belong to the category of performance measures.

<i>Brand Funnel Construct</i>	<i>Illustrative Endogenous Variables</i>	<i>Illustrative Studies</i>	<i>Empirical Findings</i>
<i>Awareness</i>	Product awareness, Interest in products	BICKART and SCHINDLER (2001); DE BRUYN and LILIE (2008)	EWOM volume and valence foster product awareness and interest.
<i>Attitude</i>	Attitude towards product/brand	NAMBISAN and WATT (2011); PAN and CHIOU (2011); WANG et al. (2012); SEN and LERMAN (2007)	EWOM volume and valence strengthen attitude towards the product/brand. Negativity bias for utilitarian products.
<i>Trust</i>	Brand trust, retailer trust, online trust	ALJUKHADAR et al. (2010); BART et al. (2005); BRODIE et al. (2011)	EWOM exchange fosters community, product, and brand trust. By increasing perceived social presence, firms can enhance this effect.
<i>Value</i>	Perceived value, product evaluation	CHAKRAVARTY et al. (2010); GRUEN et al. (2006)	EWOM increases product evaluations and perceived value. EWOM is more persistent than professional reviews.
<i>Purchase</i>	Purchase intention, consumer preferences, need recognition	ADJEI et al. (2009); DE VALCK et al. (2009); AGGARWAL and SINGH (2013); DECKER and TRUSOV (2010); PARK et al. (2007); PARK and LEE (2009); JIMÉNEZ and MENDOZA (2013); BENLIAN et al. (2012); PARRY et al. (2012)	The eWOM effect of volume and valence is valid in all decision making phases. This effect is higher for earlier decision stages. Quality and reliability issues show the highest impact on purchase intention. EWOM shows high effect on purchase intention. EWOM and traditional WOM both able to trigger purchase intent.
<i>Adoption/Choice</i>	Product adoption, Product choice, choice optimality, choice behavior	DE BRUYN and LILIE (2008); THOMPSON and SINHA (2008); GUPTA and HARRIS (2010); NARAYAN et al. (2011); SENEAL and NANTEL (2004); SMITH et al. (2005); DEWAN and RAMAPRASAD (2012)	EWOM volume and valence foster product adoption and act as information surrogate that reduces inherent choice insecurity. It decreases the time to adopt and the likelihood that customers switch to competitors.
<i>Satisfaction/Commitment</i>	Satisfaction/Commitment	BRODIE et al. (2011)	EWOM volume and valence positively influence satisfaction and commitment
<i>Loyalty</i>	Behavioral loyalty	GARNEFELD et al. (2010); GRUEN et al. (2006); JANG et al. (2008); SCARPI (2010)	EWOM volume and valence increase behavioral loyalty dimensions including WOM behavior and repurchase rates.

Table 4: Effects of eWOM on Consumer Mindset Metrics

Research on the effects of eWOM on consumer mindset metrics is closely related to the variables discussed in the chapter above. EWOM valence is primarily used since the research stream is dominated by experimental setups. However, other variables like social presence of websites (e.g., AHLUWALIA, 2002) or consumer engagement with communities (e.g., BRODIE et al., 2011, THOMPSON and SINHA, 2008) are also applied.

Awareness. By means of an online experiment over a 12 week period, BICKART and SCHINDLER (2001), as one of the oldest studies in the sample at hand, show that the interest in a product category (i.e., cycling, exercise, nutrition, photography, and stereo equipment) can be fostered

when people are interacting with discussion forums. Interacting with a corporate website showed significantly smaller effects. Product interest and awareness can further be enhanced by eWOM from friends and acquaintances independent from any platform. DE BRUYN and LILIEN (2008) showed in their experimental setup that viral e-mail chains, induced by 634 student initiators, are able to create higher product awareness and even create an above average interest in the topic, offer, product, or service recommended.

Attitude. Further down the brand funnel, NAMBISAN and WATT (2011) show with data from 206 users of the forums of Intel, IBM, Microsoft and Adobe that the higher a consumer's exposure with product, brand, or service-related eWOM exchange, the better his attitude towards the brand and products. Even though their study only examines the IT sector, the authors add that it has to be kept in mind that eWOM exchange platforms are increasingly becoming a "lounge" area for customers to hang out and talk to one another. Therefore, online communities can play a crucial role in shaping customers' perceptions regarding the product, service, or brand discussed. An influence of eWOM valence on attitudinal measures was observed in the experimental studies of PAN and CHIOU (2011), and SEN and LERMAN (2007). Both studies confirm the influence of valence onto people's attitude towards a product or brand. The negativity bias could be shown for utilitarian products (i.e., PDAs) in the lab setting (SEN and LERMAN, 2007, p. 76). By means of an online questionnaire sampling within Chinese social media users, WANG et al. (2012) further confirm that positive discussions on social media platforms are able to increase respondents' attitude toward the product. The reported eWOM effect appears to be stronger for consumers who scored low in their need for uniqueness.

Trust. By means of their netnographic analysis of 427 posts from an internet platform of a whole body vibration device between the years 2006 and 2008, BRODIE et al. (2011) showed that trust measures could be increased when consumers showed a higher engagement in virtual brand communities. Sharing knowledge and content through eWOM, learning from others by consuming eWOM, as well as simple socializing factors foster higher levels of trust towards the community, the brand, and its product. ALJUKHADAR et al. (2010) and BART et al. (2005) add that companies have the opportunity to elevate trust measures through website design aspects. By means of experimental setups and SEM, they both argue that the perceived social presence of sections like privacy disclosure, navigation, and order fulfillment enhance trust measures towards the website, brands and products presented.

Value. Pre-release product evaluations, as an indicator of perceived product or service value, are also significantly increased after the exposure to eWOM messages. CHAKRAVARTY et al.

(2010) reported within their experimental setup that movie evaluations from other consumers are even more persistent than professional critic reviews. In their study, infrequent moviegoers are more influenced by eWOM than frequent moviegoers. Whereas all studies hypothesize that WOM is highly capable to influence the receivers' way of thinking about a product or brand, GRUEN et al. (2006) explicitly provide evidence for a change in perceived value of a firm's offerings. Their questionnaire within participants of a company-independent internet forum of a software product for video editing revealed that consumer-to-consumer interactions positively affect the perceived value of a firm's offerings. Therefore, eWOM can be seen as a strong source of information for internet users that can even tip the balance pro or con an actual purchase decision.

Purchase. Through regression and conjoint analysis, DECKER and TRUSOV (2010) provide evidence for eWOM's capability to form overall consumer preferences. They show a connection between topics discussed in eWOM communications and the resulting overall consumer preferences, operationalized as the sum of rating measures available. Reliability topics and quality issues in consumer reviews show the highest influence on consumer preferences. By using a dataset of disclosed deal flow data of venture capitalists, AGGARWAL and SINGH (2013) could also show that the volume of blog coverage increases the probability with which an entity passes the screening stage of a venture capitalist. The authors conclude that the decision making process of a venture capitalist is also influenced by eWOM discussions. When it comes to the purchase decision, literature also provides evidence of a considerable eWOM effect. All decision making phases from need recognition to post-purchase evaluation are influenced by the frequency of interaction with an online community. This was shown by DE VALCK et al. (2009) by means of a large scale questionnaire within about 1,000 participants of a recipe exchange community. The more interaction with the community, the more positive influence could be observed. The positive effect of eWOM volume, valence, and review quality on a receiver's purchase intention was also confirmed by other experimental contributions (PARK et al., 2007, PARK and LEE, 2009, ADJEI et al., 2009). In addition, JIMÉNEZ and MENDOZA (2013) add that the level of detail in eWOM messages actually increases the eWOM effect. The experimental setup with a fictitious shopping task of BENLIAN et al. (2012) revealed that the eWOM effect is considerably strong in influencing the preceding constructs of trust and affective beliefs before positively influencing purchase intent. PARRY et al. (2012) used an online questionnaire to investigate the eWOM effect of over 1,200 Japanese customers of consumer electronics. They show that both traditional and electronic WOM are able to

positively influence purchase intention. In addition, eWOM is more persistent in the case of high social or symbolic consumption (i.e., smart phone).

Adoption/Choice. As many studies confirmed the positive effect of eWOM on measures like purchase intention, it is not a long stretch to assume a similar positive effect on product adoption. THOMPSON and SINHA (2008) could show by a large scale regression with close to 100,000 eWOM messages extracted from four major IT brand communities (i.e., Intel, AMD, ATI, NVIDIA) that the adoption of new products is enhanced by eWOM and community engagement. It takes less time for people to adopt and additionally decreases the likelihood that participants will switch to a new product from a competing brand. DE BRUYN and LILIEN (2008) confirm these findings and report that consumer-to-consumer recommendations not only in communities but also via email foster recipients' product adoption. NARAYAN et al. (2011) investigate the effects on people's product choices. Within their choice-based conjoint experiment they come to the conclusion that consumers' weight on their own preferences diminishes with an increasing number of peer influencers. They find evidence for an attribution within consumers' uncertainty about the importance of certain product attributes when facing a specific choice decision. EWOM acts as an information surrogate to fill this gap. In line with this argumentation, GUPTA and HARRIS (2010) argue that with an increasing number of eWOM messages the time spent to consider the eWOM messages and the total time spent on the decision task also increases. Moderated by the construct of "need for cognition", the presence of eWOM messages can, under certain circumstances (i.e., low need for cognition), significantly reduce choice optimality. Even though GUPTA and HARRIS (2010) only use pWOM as a treatment and only rely on one product (i.e., laptop), the results indicate that outside of laboratory setting where a multitude of distracting information is present, the effect of eWOM on consumer preferences or choice can be different and even guide consumers into a suboptimal decision. In general, people perceive eWOM messages from other consumers as more convincing and trustworthy when compared with IT-based recommendation systems or human expert referrals (SENECAL and NANTEL, 2004). UGC also shows higher influence onto consumers' actual choice behavior (SMITH et al., 2005). However, SENECAL and NANTEL (2004) report that with regard to the actual purchase consequences, algorithm-based recommendation systems show a higher influence on people's choice behavior than advice from other consumers or human experts. DEWAN and RAMAPRASAD (2012) investigated the effect in a music setting. They combined data of music sampling frequency as proxy for consumer preferences with data from 281 blogs posting between 07/2006 – 08/2006, Amazon reviews, and sales rank data. Blog popularity was found to have a stronger association with music

sampling in the case of niche compared with mainstream music. The more popular or visible a music blog becomes, the higher its effect on music sampling.

Satisfaction/Commitment/Loyalty. According to OLIVER (1999, p. 34), loyalty, satisfaction, and commitment are closely related concepts that form one of the most beneficial corporate goals: to enhance repurchase rates and to lower defection rates to increase net present value. Within their netnographic study, BRODIE et al. (2011) find that consumer engagement in brand communities leads to a higher customer satisfaction, commitment, and higher loyalty to the brand. The engagement in an online community as well as the participation within eWOM discussions increases behavioral loyalty dimensions (GARNEFELD et al., 2010, JANG et al., 2008, SCARPI, 2010). GRUEN et al. (2006) confirmed the eWOM effect on the loyalty dimensions of repurchase and WOM behavior using data from a forum for video editing.

Even though the research section looking at the effects on the consumer mindset broadly accepts the existing link between volume and the consumer mindset (e.g., CHAKRAVARTY et al., 2010, p. 185), emphasis is clearly put on valence measures. Through the application of mainly laboratory experimental setups, studies concentrate on the investigation of theoretical effects with high internal but low external validity. Distracting information comparable to a real life setting in the web 2.0 environment is often neglected. Besides these methodological deliberations it is noticeable that no single study investigates the effects of eWOM on brand image measures. Even though brand image is typically not included in market response models, partly because they are difficult to measure reliably and in a consistent way across different product categories (SRINIVASAN et al., 2010, p. 681), it still has great significance in consumer behavior research and enormous predictive potential to indicate ramifications of eWOM (DOBNI and ZINKHAN, 1990, p. 118). The purely positive results in this chapter might of course be a result of a publication bias. But the reported outcomes also show similarities to effects that have already been reported within traditional WOM and advertising literature (cf. e.g., AHLUWALIA, 2002, p. 278, WESTBROOK, 1987, p. 268). This poses the question if the proven effects along the brand funnel can be taken as granted and generalizable. If and how these relationships sustain within a real life setting outside of artificial situations has to be looked at by means of subsequent field experiments.

4.2.2 EWOM and Product and Market Performance

Drawing from signaling theory, ERDEM and SWAIT (1998, p. 131) show that brand related communication activities, such as eWOM, pay into a change of each individual's mindset and

behavior. The sum of those changes, therefore, triggers measurable performance indicators on product and brand level such as sales, market shares, or price premiums (GUPTA and ZEITHAML, 2006, pp. 722-724). Following KELLER and LEHMANN (2006, p. 754), product and market performance measures are the observable result of “*what customers do*”. The articles in this section all treat eWOM as an exogenous variable and try to explain observable market performance outcomes on an aggregated product, company or brand level. Table 5 presents the identified studies sorted by their product performance measure used as dependent variable.

The majority of studies operationalize product and market performance mostly by means of online and/or offline sales data or use accessible online sales ranks from big online retailers. As the studies deal with the aggregated consumer preferences and their manifestation on the market, large scale panel regression is the dominating method. Datasets often consist of more than 100,000 observations (e.g., FORMAN et al., 2008, LI and HITT, 2008). Thus, valence coding by hand is mostly not conducted. Valence operationalization is dominated by ratings taken from online retailers (e.g., GU et al., 2011), movie review sites (e.g., DELLAROCAS et al., 2007), or blogs (e.g., DHAR and CHANG, 2009).

<i>Product Performance Measure</i>	<i>Illustrative Dependent Variables</i>	<i>Illustrative Studies</i>	<i>Empirical Findings</i>
<i>Online Sales Ranks</i>	Amazon sales rank, online album charts	AMBLEE and BUI (2008)	Positive effect of volume
		LI and HITT (2008)	Positive self-selection bias found
		CHEN et al. (2004)	No effect of valence (ratings)
		DHAR and CHANG (2009)	Valence effect (ratings) < volume
		CHEVALIER and MAYZLIN (2006)	Mixed effect of volume, positive effect of valence (ratings), nWOM > pWOM, no effect of length
		CHEN et al. (2011b)	NWOM has negative effect, pWOM only vague evidence (ratings)
		FORMAN et al. (2008)	Positive effect of valence (ratings)
		PATHAK et al. (2010)	Positive effect of volume, positive effect of valence (ratings)
		GU et al. (2011)	Positive effect of internal and external volume and valence (ratings)
		GU et al. (2013)	Valence (ratings) positive effect, positivity effect for popular products
<i>Online Sales</i>	Online sales data from retailers	ETZION and AWAD (2007)	Positive effect of valence (ratings), volume only when valence does not differentiate
		MOE and TRUSOV (2011)	Positive short term effect of valence (ratings) and indirect effect (+) dispersion
<i>Offline Sales</i>	TV-viewership rating, box office ticket sales or revenues, election results	DUAN et al. (2008a)	Positive effect volume, no valence (rating)
		DUAN et al. (2008b); LIU (2006)	Positive effect of volume; no effect of valence (hand-coded)
		GODES and MAYZLIN (2004)	Positive effect of volume in later periods, no effect of valence (hand coded), dispersion positive effect
		DELLAROCAS et al. (2007)	Positive effect of volume, valence (ratings) predicts publicity of movie
		TUMASJAN et al. (2011)	Positive effect of volume (tweets) on election results, valence (IT-coded) reflects political discussions
		ANDERSON and MAGRUDER (2012); CHINTAGUNTA et al. (2010)	Positive effect of valence (ratings); Positive effect of valence (ratings) and no effect of volume and dispersion,
<i>Total Sales</i>	Sales figures from firms	SONNIER et al. (2011)	Positive effect of valence (IT-coded), positivity bias found
		ZHU and ZHANG (2010)	Positive effect of volume, valence (ratings) and dispersion only show effect on less popular products
		STEPHEN and GALAK (2012)	EWOM volume and valence (ratings) are able to predict total sales
<i>Market Prices</i>	Prices on Amazon, average market prices	PATHAK et al. (2010) SHIN et al. (2011)	Positive effect of valence (ratings) Negative effect of nWOM (IT-coded), nWOM and pWOM both lead to price increases for low priced products

Table 5: Effects of eWOM on Product and Market Performance Measures

Online Sales Ranks. AMBLEE and BUI (2008) extracted consumer reviews from Amazon.com of nearly 400 e-books sold in 2006. By means of a logistic and a time series regression, they find a positive connection between eWOM volume and online sales rank. The positive effect of pure volume measures¹⁰ is also in line with the findings of LI and HITT (2008), who report that the number of reviews posted since product release influences sales rank data. They add that especially early consumer reviews tend to be positive which implies a positive self-selection bias people do not fully correct when they consider these early reviews in a later period. CHEN et al. (2004) also confirm these findings by an application within online book reviews from Amazon. They show a strong effect for volume, but clearly report no effect for the included consumer ratings. DHAR and CHANG (2009) pick up these thoughts within their research predicting online music album sales ranks by means of blog chatter from “Technorati”. Their main focus is to investigate differences in effect of volume, valence, and social network connectivity of an artist and contrast results to traditional reviews about new music albums. They report that eWOM volume has predictive power for online album sales ranks one and two weeks ahead, whereas eWOM valence is only able to predict sales in week t+1. Traditional critics’ reviews still have the strongest impact up to three weeks. In contrast to the findings above, CHEVALIER and MAYZLIN (2006) do not find a clear overall effect of eWOM volume. In their study on book reviews from Barnesandnoble.com and Amazon.com, they only report the effect of volume on Amazon.com. Valence measures (i.e., average star ratings) prove to be a small but significant predictor of future sales independent of the respective platform. The length of each review did not turn out to be a significant predictor. The authors, furthermore, provide evidence for the negativity bias. CHEN et al. (2011b) support these findings in their natural experiment using Amazon.com camera review and sales rank data from 2005 to 2007. With regards to eWOM volume they find that the impact of volume declines over time. The valence effect clearly dominates the reported effect for eWOM volume. FORMAN et al. (2008) also report a more stable influence of eWOM valence compared to volume measures. Clear evidence for a strong positive effect of both volume and valence is provided by the works of PATHAK et al. (2010) and GU et al. (2011). The latter even provide additional proof that product ratings and reviews from one retail website show effect on sales ranks of another platform. By means of a large scale panel dataset, GU et al. (2013) showed that consumers are more receptive to pWOM in case of popular products, whereas nWOM has a stronger negative effect on the

¹⁰ Note that volume measures, of course, are highly influenced by previously posted consumer reviews. The inherent endogeneity forms one of the major challenges for academics and is more and more addressed in publications (e.g., SONNIER et al., 2011, pp. 703-704, TRUSOV et al., 2009, pp. 91-92, CHINTAGUNTA et al., 2010, pp. 945-946). For clarity purposes, endogeneity of eWOM communication shall not be a major focus of the paper at hand.

online sales rank of unpopular products. The research group of HO-DAC et al. (2013) partly contradicts those findings by saying that pWOM (nWOM) messages show a significant positive (negative) effect on online sales rank for brands with weaker brand equity. The variance of eWOM valence ratings was found to positively influence book sales rank data on Amazon and Barnes & Noble in the difference-in-difference approach of SUN (2012) only if the average star rating was comparably low. The author adds that the variance of eWOM messages shows a significant interaction with the average valence rating. Researchers should, therefore, incorporate the interaction term of valence and variance in their methodological approaches.

In summary, evidence at hand points towards a stronger link of eWOM volume and online sales rank data. Whereas no single study neglects the influence of eWOM volume, I found plenty of works raising serious doubts concerning the effect of eWOM valence (i.e., GU et al., 2011, PATHAK et al., 2010, FORMAN et al., 2008, CHEN et al., 2004, CHEN et al., 2011b). No single study in this first subsection uses other valence measures than average ratings, which even enhances the need for an in-depth investigation of valence by content analysis. As it can be assumed that strong brand equity correlates with higher product popularity, the contradictory results of HO-DAC et al. (2013) and GU et al. (2013) are worth mentioning. They both work with panel data. For this reason, a methodological bias can at least partly be ruled out. Further research should pick up these contradictions and clarify the effect of product popularity and brand equity. The identification of a significant interaction term of eWOM valence and variance is noticeable and has to be picked up and validated by future research following SUN (2012).

Online Sales. Due to data availability reasons, there are only two studies that apply real online sales data from cooperating firms, i.e., online retailer of bath, fragrance, and beauty products (MOE and TRUSOV, 2011) as well as a large online retailer (ETZION and AWAD, 2007). Both studies confirm the positive effect of volume and also find evidence for a positive valence influence. By means of hazard models, MOE and TRUSOV (2011) investigate the impact of social dynamics in the ratings environment on subsequent rating behavior and look at the effects on product sales. They find that eWOM valence directly influences sales. However, the effect is relatively short-lived when indirect effects (i.e., eWOM volume and eWOM valence also being influenced by previously posted eWOM¹¹) are also taken into account. EWOM volume is found to have an impact on the respective sales measures. The authors also showed an indirect influence of eWOM dispersion. ETZION and AWAD (2007), in contrast, demonstrate within their

¹¹ Note that even though this dynamic is not the major focus within the paper at hand, MOE and TRUSOV (2011) seem to be the first who model the whole eWOM creation process as a dynamic construct of previous and current posts and do control for endogeneity in every stage.

time series regressions that volume is only associated with higher sales when the average product ratings are above a certain anchor point. If valence already provides enough differentiation possibilities, consumers do not take pure volume metrics into account. Thus, valence is clearly related to an increase in sales and superior to pure volume measures.

Offline Sales. Another major part of research uses offline sales data as dependent variable. Papers in this section try to show the transferability from eWOM information into the offline purchase behavior. The movie and TV industry are prevalent within the studies at hand due to vivid pre-release discussions online and relatively short product life cycles with many new products coming on the market every year. Again, time series models are the common method to analyze eWOM effects. Volume measures are, again, the strongest and most persistent predictor across all studies that use offline sales data. The volume measures of movie reviews taken from “Yahoo! Movies” are found to positively influence box office performance (DUAN et al., 2008a, DUAN et al., 2008b, LIU, 2006). The studies also reveal that the valence of reviews did not significantly influence sales and box office performance. These findings are in line with the reported effect of GODES and MAYZLIN (2004). Volume and dispersion measures of eWOM conversations in 20 “Usenet” discussion groups about new TV-shows significantly influence the TV-show’s offline sales in term of TV-ratings. Dispersion even shows a higher influence than pure volume metrics which only turn significant in the later periods of a TV-show’s lifecycle. On the contrary, the authors note that eWOM valence has no significant effect on subsequent ratings. Furthermore, the positive volume effect is also confirmed by the study of DELLAROCAS et al. (2007). They apply pre-release eWOM data from different movie review platforms (i.e., Yahoo! Movies, BoxOfficeMojo, and Hollywood Reporter) to predict box office revenues during the opening week. Valence is only found to be driving subsequent eWOM volume and merely predicts a movie’s publicity in general. TUMASJAN et al. (2011), as the only study within this paper’s sample, uses Twitter posts (i.e., tweets)¹² to forecast offline sales in terms of elections results of the 2009 federal election in Germany. They come to the conclusion that the volume of tweets predicts election results even better than traditional voting polls. The valence of tweets is able to provide a textual manifestation of the election campaigns. Besides the solely positive volume effects reported by studies above, CHINTAGUNTA et al. (2010) demonstrate that eWOM volume and dispersion taken from the Yahoo! Movies platform is not related to box office ticket sales. Moreover, eWOM valence turns out to be strong, significant predictor of subsequent opening earnings and box office performance. EWOM valence,

¹² JANSEN et al. (2009, p. 2186) confirm that tweets form eWOM limited to 140 characters at a time.

operationalized as star ratings from the restaurant review platform Yelp, also shows a strong impact in the study of ANDERSON and MAGRUDER (2012). The regression discontinuity design revealed that an extra half-star rating means that restaurants sell out 49% more frequently. The effect was found to be especially strong if alternative resources of information about the restaurant were scarce.

In summary, volume once more turns out to be the most important measure that influences offline sales. Only two studies could show a small effect of valence (i.e., DELLAROCAS et al., 2007, TUMASJAN et al., 2011) and two studies speak of a high influence of eWOM valence metrics (i.e., CHINTAGUNTA et al., 2010, ANDERSON and MAGRUDER, 2012). Interestingly, GODES and MAYZLIN (2004) and LIU (2006), as the only two studies within this paragraph that apply a valence classification by hand-coding, clearly show no effect of valence onto the respective offline sales measures. There seems to be evidence that consumers do not process the whole information inherent in a specific review when rating measures are available to reduce information processing costs or simply save time.

Total Sales. Three studies focus on eWOM effects on total firm sales. SONNIER et al. (2011) analyzes the effects of chatter about one technical firm on their total sales volume. They report that chatter valence shows a significant effect on sales. The authors find a “positivity bias” so that pWOM has a higher effect size than nWOM. They argue that these results are in line with behavioral research that confirms the higher persuasiveness of pWOM in case of a familiar brand (cf. AHLUWALIA, 2002, p. 278). However, the majority of studies that search for differences in pWOM and nWOM effect strengths conclusively report a negativity bias (e.g., CHEN et al., 2011b, SEN and LERMAN, 2007). SONNIER et al. (2011) further state that the aggregation of eWOM messages across valence masks the real effects on sales. They suggest that, although obtaining the sentiment analysis data is costly relative to publicly available data on the total volume of comments, it improves predictive power of their proposed eWOM model. ZHU and ZHANG (2010) try to predict total sales of Xbox and Playstation 3 game sales by posts on gamespot.com. Volume has a positive influence on sales of all games that demand an online connection of the player. Surprisingly, no effect was found on sales of games that can also be played offline. In addition, eWOM valence and dispersion only drive sales for less popular games. A positive effect was found for valence and a negative effect for dispersion. The authors suggest that datasets with different product types, even for the same product category, could lead to different conclusions. STEPHEN and GALAK (2012) applied a large scale panel regression with data from an online marketplace for microloans. Using the eWOM data from blogs and

discussion forums, they could show that valence ratings indeed affect sales. They state that even though both traditional media and eWOM show a positive effect on sales, eWOM's sales elasticity is significantly greater due to the higher frequency of eWOM discussions.

Market Prices. EWOM valence can have a positive effect on market prices (PATHAK et al., 2010). PWOM allows retailers to charge higher prices whereas nWOM, naturally, leads to a decrease. SHIN et al. (2011) analyze the interplay between online chatter about MP3 players, the inherent quality perceptions, and the respective market price. They confirm the negative effect of nWOM and the positive effect of pWOM. The authors also add that the effect of pWOM (nWOM) is higher for low (high) priced products. The market leader's market prices decline stronger by negative chatter, whereas the following brands benefit more than the market leader from positive statements on the internet.

The diverse results in this chapter unveil that across all studies the inherent problem of endogeneity seems to be the greatest challenges. As eWOM proved efficacy to drive sales, the resulting sales, again, increase subsequent eWOM volume. Studies more and more model eWOM as a dynamic process in order to tackle this inherent problem (MOE and TRUSOV, 2011, p. 447). Reported results might also be a consequence of some hidden latent variable that was simply not considered within any empirical approach. Those constructs could be e.g., corporate reputation (AMBLEE and BUI, 2008, p. 11), perceived quality and value (STEPHEN and TOUBIA, 2010, p. 226), or new product launches (MCALISTER et al., 2011, p. 9). Taking into account that the majority of empirical attempts works with fixed or random effects, they are to some extent able to mitigate correlations with unobservable variables in the background (HARTMANN et al., 2008, p. 294). Interestingly, hand-coded valence measures show no effect on product performance measures and market prices (GODES and MAYZLIN, 2004, LIU, 2006). Consumers do not process all information but tend to rely on simpler heuristics like rating systems. Volume seems to be the more stable influencing factor across all studies and methods. One reason for this finding might be that “[...] *when the valence does not convey enough information to differentiate products, the volume becomes a significant factor in consumers' purchase decisions*” (ETZION and AWAD, 2007, p. 11). Nevertheless, CHINTAGUNTA et al. (2010, p. 956) emphasize that their findings about a positive influence of valence and no effect of volume reverses previously established findings in this domain. This especially highlights the importance to academically continue the ongoing discussion.

The effects of the previous chapter, of course, cannot be seen as generalizable across all industries and product categories. The majority of studies uses classical experience goods (e.g.,

books, TV-series, movies, video-games) to analyze eWOM effects. The influence of eWOM differs, when e.g., search or credence qualities come into play or different shopping goals (e.g., utilitarian vs. hedonistic) of consumers are taken into account. Chapter 4.3 will present these moderating effects in more detail.

4.2.3 EWOM and Financial Performance

The effects of eWOM on financial performance measures form the last step of the investigation along the value chain. Financial performance measures, as *how financial markets react*, are of crucial interest to CFOs or CEOs unlike the majority of marketing metrics (KELLER and LEHMANN, 2006, p. 754, GUPTA and ZEITHAML, 2006, p. 719). Fifteen articles could be identified that treat eWOM as an exogenous construct and analyze effects on financial performance measures. The majority of studies in this paragraph use eWOM about stocks extracted from stock message boards (e.g., Yahoo! Finance or Raging Bull) as independent variable. As stock-eWOM follows a similar logic like e.g., analyst forecasts and other information sources about the stock market, the effect of buy/hold/sell recommendations on these platforms follows a different rationale than UGC within a purchase decision or product choice. To enable comparison possibilities to previous and following chapters, pure stock-eWOM shall be neglected in this paragraph. Nevertheless, Table 6 presents all 15 papers sorted by their dependent financial performance measure and splits up regarding their eWOM type used. Due to the comprehensiveness of studies, many papers have to be displayed multiple times.

<i>Financial Performance Measure</i>	<i>Illustrative Dependent Variables</i>	<i>Illustrative Studies</i>	<i>Empirical Findings</i>
<i>Stock Return/ Firm Value</i>	Abnormal stock returns, stock price, excess return	<u>Stock eWOM</u> WYSOCKI (1999); THAPA and BIRD (2010); TUMARKIN and WHITELAW (2001); COOK and LU (2009); ANTWEILER and FRANK (2004); DAS and CHEN (2007); OH and LIU SHENG (2011); BIRD and THAPA (2011)	Positive effect of eWOM volume, no effect of eWOM volume, negative effect of eWOM volume, positive effect of eWOM valence (ratio/IT), negativity effect was found
		<u>General eWOM</u> HU et al. (2011); MCALISTER et al. (2011); TIRUNILLAI and TELLIS (2012); LUO and ZHANG (2013); LUO et al. (2013b); CHEN et al. (2012); HU et al. (2012)	Positive effect of volume and blog visibility, negativity effect (IT), positive effect for eWOM volume and valence (ratings), strongest pre-release, low blog visibility leads to higher stock returns
<i>Stock Volatility/ Risk</i>	Idiosyncratic risk, conditional volatility	<u>Stock eWOM</u> DAS and CHEN (2007); BIRD and THAPA (2011); ANTWEILER and FRANK (2004)	Positive effect of eWOM volume
		<u>General eWOM</u> TIRUNILLAI and TELLIS (2012); LUO and ZHANG (2013); LUO et al. (2013b); CHEN et al. (2012)	Positive effect of volume and competitor chatter, negative effect of nWOM (IT), positive predictive power of eWOM valence (ratings) and volume
<i>Trading Volume</i>	Daily turnover	<u>Stock eWOM</u> TUMARKIN and WHITELAW (2001); ANTWEILER and FRANK (2004); DAS and CHEN (2007)	Positive effect of eWOM volume, negative and no effect of dispersion
		<u>General eWOM</u> HU et al. (2011); TIRUNILLAI and TELLIS (2012)	Positive effect of eWOM volume, nWOM (IT), and blog visibility

Table 6: Effects of eWOM on Financial Performance Measures

Stock Return/Firm Value. MCALISTER et al. (2011) did not focus on stock message boards but scraped the whole internet in order to extract general, stock-unrelated eWOM messages. They find that the volume of total and neutral chatter both have a positive effect on stock returns. TIRUNILLAI and TELLIS (2012) extracted company and product related UGC from online shopping platforms and found that pure volume measures have the strongest relationship with stock returns both in the short and long term. Furthermore, they confirmed the asymmetric impact of valence measures on stock returns. The negative effect of nWOM, again, is stronger than the positive consequences of pWOM. Interestingly, this assumption only holds true for the IT-coded valence measures and is non-existent for numerical ratings (i.e., Amazon star ratings). LUO et al. (2013b) also confirm those results using a panel-dataset of nine IT hard and software companies. They argue that eWOM volume and valence (ratings) are leading indicators for firm equity value. EWOM is found to be superior to other social media metrics like Google searches or web traffic (cf. also LUO and ZHANG, 2013). Especially valence ratings show high predictive

power. By means of an event study in the movie industry, CHEN et al. (2012) confirm that eWOM exerts significant impact on stock returns in the direction of their valence (ratings). The effect is strongest pre-release. As soon as sales data become available, the eWOM effect diminishes. Furthermore, HU et al. (2011) found that the visibility of a company across blogs is positively associated with the respective firm's value. However, one year later, HU et al. (2012) report different results. Using a similar dataset they argue that companies with low blog visibility actually realize higher returns than do companies with a comparably higher blog visibility. The effect holds true even when controlling for other risk factors and traditional media coverage and is more prominent for stocks with low institutional ownership. They argue that the blog effect can be attributed to the limited attention theory and cannot be arbitrated due to investors' self-attribution and short-sale constraints.

Stock Volatility/Risk. TIRUNILLAI and TELLIS (2012) show that eWOM volume positively influences stock volatility. In addition, negative valence information in IT-coded UGC messages causes a significant increase in idiosyncratic risk. The authors also showed that chatter about a competitor is capable to influence a firm's risk measures. These results are confirmed by LUO et al. (2013b) and LUO and ZHANG (2013) with very similar datasets.

Trading Volume. Again, eWOM volume induces subsequent trading. The more people talk about a specific company's products and services, the more shares will be traded. In addition, IT-coded nWOM messages also elevate trading quantity in both the short and long term (TIRUNILLAI and TELLIS, 2012). HU et al. (2011) report that trading volume is also caused by a company's blog visibility.

In summary, stock-unrelated eWOM has the potential to predict stock returns. Due to the lack of perfect information, investors use the information on different platforms and on the web in general (TIRUNILLAI and TELLIS, 2012, p. 213). Again, nWOM has higher predictive accuracy than pWOM (TIRUNILLAI and TELLIS, 2012, p. 213). In addition, pWOM and nWOM were found to be highly correlated which might be a symptom of the nature of online communication, where praise can be met swiftly with scorn and vice versa (MCALISTER et al., 2011, p. 10). It is still questionable if blog visibility shows a positive or a negative effect on firm value. Further clarification of the discussion raised by HU et al. (2011) and HU et al. (2012) is needed and a replication seems promising.

4.3 Moderators of the Main Effects

CHEUNG and THADANI (2012, p. 464) provide an overview of eWOM communication by the application of a classical stimulus response model adapted from HOVLAND (1948). They argue that the process of eWOM communication consists of the communicator (i.e., the sender), the stimulus (i.e., the message transmitted), the receiver (i.e., the individual who responds to the communication), and the response itself that is triggered by the respective message. Three arguments make it necessary to adjust the proposed framework for the paper at hand. First, the authors see the communicator as independent from the respective stimulus he sends. This remains doubtful taking into account that social media users decide themselves what they write or review about. Second, CHEUNG and THADANI (2012) state that platform effects (e.g., Facebook vs. blog vs. forum) only influence the degree of eWOM adoption. As it can be assumed that platforms, especially discussion boards or forums are mostly topic specific (cf. e.g., DE VALCK et al., 2009, NAMBISAN and WATT, 2011), the contextual factors have to be considered much earlier than in the stage of the actual response measure. Third, the authors use the framework to sort both, moderator effects and actual eWOM outcomes, whereas in this paper only moderator effects shall be categorized. And fourth, they only focus on individual-level eWOM research as a directed interpersonal approach. The paper at hand uses both, individual and market-level studies as its source for systematization. Thus, the proposed framework of CHEUNG and THADANI cannot be transferred directly to systematize the identified moderators of the main effects in the upper chapters. It has to be customized to fit this paper's approach. Figure 2 provides an overview of the proposed classification.

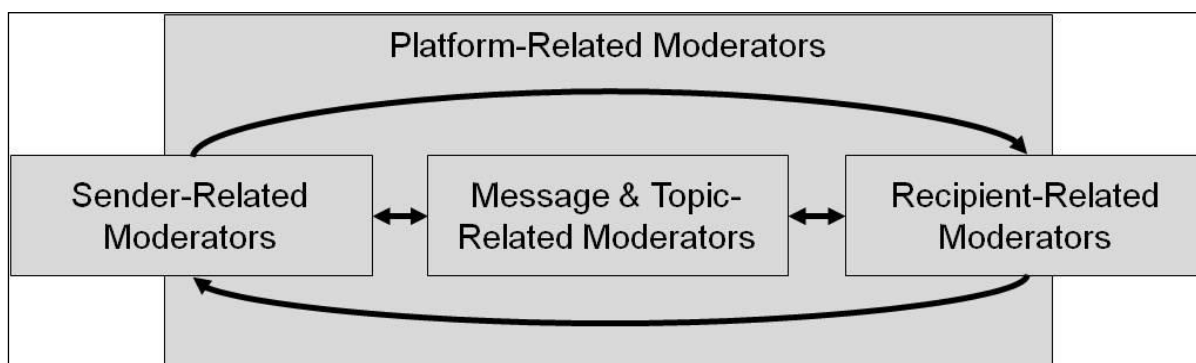


Figure 2: Framework for Moderator-Effects

Table 7 provides an overview of the identified moderators of eWOM effects along the social media value chain sorted by the types of moderators presented in Figure 2. The articles in this paragraph come from the research area of consumer mindset metrics and product market performance. Because of their major focus on stock-chatter, financial performance literature does not add to the moderators extracted in this chapter.

<i>Type of Moderator</i>	<i>Illustrative Moderators</i>	<i>Illustrative Studies</i>	<i>Empirical Findings</i>
<i>Sender-Related</i>	Expertise & Trustworthiness	SENECAL and NANTEL (2004); SMITH et al. (2005); ADJEI et al. (2009)	↑expertise and trust→↑eWOM effect
	Product Experience	GARNEFELD et al. (2010)	↓experience→↑ eWOM effect of sending
	Credibility Information disclosure	COOK and LU (2009) FORMAN et al. (2008)	↑credibility→↑eWOM effect ↑disclosure→↑eWOM effect
<i>Relationship of Sender & Receiver</i>	Tie strength	DE BRUYN and LILIE (2008); PAN and CHIOU (2011) SMITH et al. (2005)	↑tie strength →↑eWOM effect
	Demographic similarity	DE BRUYN and LILIE (2008)	↑dissimilarity→↑eWOM effect
	Geographical proximity	FORMAN et al. (2008)	↑proximity→↑eWOM effect
<i>Recipient-Related</i>	Consumption goal (regulatory focus)	ZHANG et al. (2010)	↑promotion (prevention) focus→ ↑pWOM (↑nWOM) effect
	Product/Brand experience	ADJEI et al. (2009); CHAKRAVARTY et al. (2010)	↓product and brand experience→ ↑eWOM effect; ADJEI et al. (2009) report opposite
	Gender	BICKART and SCHINDLER (2001)	eWOM effect higher for females
	Internet proficiency	DE VALCK et al. (2009); THORBJØRNSEN et al. (2002)	↑internet proficiency→↓eWOM effect
	Need for cognition	GUPTA and HARRIS (2010)	↑higher NFC→↑eWOM effect
	Need for uniqueness	WANG et al. (2012)	↓lower NFU→↑ eWOM effect
	Product involvement	PARK et al. (2007)	↓involvement→↑eWOM volume rather than review quality
Shopping goal	SMITH et al. (2005)	↑utilitarian shopping goal (↑hedonistic)→↑effect of eWOM (↓eWOM effect)	

Table 7: Moderators of eWOM Effects

<i>Type of Moderator</i>	<i>Illustrative Moderators</i>	<i>Illustrative Studies</i>	<i>Empirical Findings</i>
<i>Message & Topic-Related</i>	Product complexity	ADJEI et al. (2009)	↑complexity→↑eWOM effect
	Product types	PAN and CHIOU (2011); PARK and LEE (2009); SEN and LERMAN (2007); SENEAL and NANTEL (2004); BENLIAN et al. (2012); JIMÉNEZ and MENDOZA (2013)	↑eWOM effect for hedonic, and experience goods. Negativity effect ↑for credence and experience goods ↑eWOM effect for experience goods ↑eWOM detail→↑ effect for search than experience goods
	Consumption type → symbolic/social	PARRY et al. (2012)	↑eWOM effect when product is consumed socially visible (Iphone)
	Recency and obscurity of recommendation	PATHAK et al. (2010) SHIN et al. (2011)	↑recency & ↑obscurity→↑eWOM effect ↑price→↑ nWOM effect
	Price of product/brand	SHIN et al. (2011); ZHU and ZHANG (2010);	↑popularity→↑nWOM effect & ↓pWOM effect
	Brand and product popularity	DEWAN and RAMAPRASAD (2012)	↑eWOM effect for niche vs. mainstream products
	Brand equity	HO-DAC et al. (2013)	↑eWOM effect for brands with low brand equity
<i>Platform-Related</i>	Platform type (user vs. corporate initiated)	ADJEI et al. (2009); BICKART and SCHINDLER (2001); JANG et al. (2008); SENEAL and NANTEL (2004)	User (company) initiated→↑(↓) eWOM effect; ADJEI et al. (2009) and SENEAL and NANTEL (2004) report no difference
	Website reputation	PARK and LEE (2009)	↑reputation→↑eWOM effect
	Brand community size	SCARPI (2010)	↓size→↑eWOM effect
	EWOM source	GU et al. (2011)	External > internal eWOM

Table 7 continued: Moderators of eWOM Effects

Sender-Related. As eWOM messages are produced by other consumers and social media users, characteristics of the sender play a huge role in influencing the strength of a respective eWOM message. Certain information about the sender can increase or decrease the penetrating power. Perceived expertise/trustworthiness of an eWOM sender increases the effect on consumer mindset metrics like uncertainty reduction, trust, or product choice decision (cf. ADJEI et al., 2009, SMITH et al., 2005, MAYZLIN, 2006). The more information is disclosed about an eWOM creator by a specific social media platform, or by the sender himself, the higher the perceived source credibility which also transfers into aggregated sales data (FORMAN et al., 2008). GARNEFELD et al. (2010) report, sending out eWOM messages also enhances the sender's affective commitment and behavioral loyalty to a brand or company. This effect is stronger for eWOM senders with low product or brand experience.

Relationship of Sender & Receiver. Sender and receiver of eWOM messages are not isolated from each other (e.g., Facebook friends) in the social media environment. A strong social relationship in an online setting between eWOM creator and receiver can be a result of their

connection in the offline world or a strong established connection in the specific online setting. Social tie strength exerts a positive influence on the strength of eWOM recommendations. The stronger the tie between sender and receiver, the higher the identified effect on product awareness measures (DE BRUYN and LILIEN, 2008), credibility and helpfulness of messages (PAN and CHIOU, 2011), and product choices (SMITH et al., 2005). DE BRUYN and LILIEN (2008) add, that when it comes to demographic similarities, it is not always the most similar person that has the highest influence on recipients. Dissimilar ties are found to be more influential than demographically similar ones across different stages of the decision-making process. Book recommendations collected from Amazon proved to be more effective when sent by a consumer that shows geographical proximity to the eWOM receiver (FORMAN et al., 2008). It makes eWOM messages more helpful and transfers more strongly into actual online sales data. Information given about eWOM senders may be used to develop social categorizations such as those based on geographic location, which enhances common identity (FORMAN et al., 2008, p. 309).

Recipient-Related. The heterogeneousness of eWOM receivers within the social media environment feeds the discussion about recipient related moderators. Personality traits and attitudes form the most important attribute used to operationalize these individual differences. Messages that confirm prior attitudes, experiences, abilities, and beliefs enhance the influence of UGC. Within laboratory experiments this could be shown for the regulatory focus as consumption goal (ZHANG et al., 2010), need for cognition (GUPTA and HARRIS, 2010), or internet proficiency (DE VALCK et al., 2009, THORBJØRNSSEN et al., 2002)¹³. The experiment of BICKART and SCHINDLER (2001) revealed a slight tendency that the effects of UGC on the consumer mindset are stronger for female participants. The actual previous experience with a product or brand was also found to negatively moderate the effect of UGC. Three laboratory experiments of CHAKRAVARTY et al. (2010) using simulated movie review platforms reveal that movie going frequency as proxy for product experience negatively moderates the effect of user generated movie reviews. The less experienced people are with a specific product or brand, the higher the influence of eWOM on perceived pre-release product value. Surprisingly, ADJEI et al. (2009) report the contrary. Using survey data from two woodworking equipment forums, they find that perceived eWOM quality leads to more uncertainty reduction for those with higher personal expertise. The authors reason this effect with the high specificity of the

¹³ Note that even though DE VALCK et al. (2009) do not use an experimental setup, they report a weak, significant, and negative effect of internet proficiency ($p < 0.1$) on different decision making phases in their regression analysis.

equipment and a better ability of experienced users to sift through large amounts of information. Dependent from receivers' shopping goal, SMITH et al. (2005) show that the influence of sender's expertise and rapport between sender and receiver changes. Consumers with a utilitarian shopping goal put more weight on a sender's expertise, whereas hedonistic shoppers prefer eWOM from strong ties. By means of a structural equation model using Chinese social media users, WANG et al. (2012) investigate the moderating effect of need for uniqueness. People that score low in their need for uniqueness are found to be influenced more strongly by eWOM messages. People who emphasize uniqueness want to differentiate themselves more and realize consumption decisions that are less dependent on sources like eWOM, but based on their own preferences.

Message & Topic-Related. EWOM metrics like volume, length, valence, or dispersion can essentially be seen as a classical moderator of social media communication where e.g., the valence of a post positively moderates the subsequent effects of eWOM. As chapter 4.1 specifically deals with different ways to operationalize eWOM, this paragraph contains exceeding factors beyond classical UGC metrics. PATHAK et al. (2010) report a significantly higher effect of eWOM taken from Amazon.com and Barnesandnoble.com when the recommended item is new. They add that the obscurity of a recommended product also positively moderates the influence of online recommendations on online sales ranks. ADJEI et al. (2009) find that eWOM about a more complex product has a higher influence on receivers' consumer mindset than UGC about less complex goods or services. The use of eWOM as quality signal reduces inherent choice complexity and acts as information surrogate for a product's hardly observable quality. Negative discussions show a larger effect-size when the product is higher priced or more popular (ZHU and ZHANG, 2010, SHIN et al., 2011). However, DEWAN and RAMAPRASAD (2012) and HO-DAC et al. (2013) find the contrary. Using large scale datasets they find that the effect of eWOM discussions and messages is higher for niche products in the music industry (DEWAN and RAMAPRASAD, 2012) and consumer electronic brands that show a lower level of brand equity (HO-DAC et al., 2013). As an interim conclusion, the majority of studies still apply UGC from the experience-good sector (e.g., computer games, restaurant guide). More generally speaking, the eWOM effect for both volume and valence measures is found to be higher when users exchange information about experience goods than search goods (SENECAL and NANTEL, 2004, BENLIAN et al., 2012). Especially nWOM is more important in the case of experience than search goods (PARK and LEE, 2009). However, the laboratory experiment of JIMÉNEZ and MENDOZA (2013) revealed that the level of detail inherent in eWOM messages shows a higher effect in case of search goods as consumers

specifically investigate different sources for in-depth information. The negativity bias is also stronger for hedonic products compared to utilitarian goods (SEN and LERMAN, 2007). SEN and LERMAN find this effect within their experimental setup with five utilitarian (i.e., PDAs) and five hedonic (i.e., movie videos) goods. They add that consumers engage more with nWOM posts in the case of a hedonic product category. Product category, thus, moderates the effect on consumers' attitude towards the product. PARRY et al. (2012) find that the type of consumption associated with a certain product plays an important role regarding the eWOM effectiveness. In their sample of Japanese consumer electronic customers they found that the eWOM effect is higher for products that are socially visible and are consumed in a symbolic way (i.e., smart phone).

Platform-Related. Contradictory results were found regarding the moderator influence of platform types. Authors hypothesize that UGC on consumer generated platforms is more relevant to consumers, can carry more empathy, and has more credibility than corporate owned vehicles (BICKART and SCHINDLER, 2001). BICKART and SCHINDLER (2001) find positive evidence that UGC creates higher product awareness and interest than company websites. JANG et al. (2008) confirm that UGC on consumer initiated brand communities shows higher information quality and has higher commitment and loyalty consequences than corporately owned forums. Contrary to those findings, ADJEI et al. (2009) and SENEAL and NANTEL (2004) report no significant difference between the eWOM effect on company-generated platforms and consumer generated platforms. PARK and LEE (2009) unveil a positive moderator effect of website reputation. They state that the effect of eWOM on established websites is higher than on unestablished websites. SCARPI (2010) adds that the size of a social media platform and its connected community negatively influences the eWOM effect on brand loyalty. He argues that small communities do operate more like a group of friends which evokes attachment and belongingness emotions that put more weight on community eWOM exchange (cf. also JAHN et al., 2011). By analyzing eWOM discussions from two different online retailers, GU et al. (2011) found that eWOM discussions also show spill-over effects. The authors extracted UGC about digital cameras from multiple product review platforms. The effect of eWOM from external platforms turned out to be more effective in predicting sales ranks on Amazon than internal consumer recommendations extracted from Amazon itself. For this reason, monitoring eWOM discussions across a broader range of platforms seems promising.

In summary, the proposed framework of Figure 2 offers a good way to classify the moderators tested along the social media value chain. Interestingly, most moderator-effects are again found

within laboratory experimental setups. It still remains questionable if the proposed effects also hold true in field studies and the more complex online environment. The role of size or popularity moderators is still unanswered. The question if eWOM is more predictive for performance measures of popular products (e.g., SHIN et al., 2011) or rather unknown products (e.g., DEWAN and RAMAPRASAD, 2012) demands further clarification.

4.4 The Company and its Dual Role

Whereas in the offline environment advertising and communication about products and brands was solely induced by the respective company, the web 2.0 landscape opens up a powerful tool for customers to independently contribute to discussions and express their opinion about product, brand, company, or service related factors. This constant and independent level of buzz makes it necessary to monitor and moderate ongoing discussions (GODES et al., 2005, p. 421). Questions of who, when, what, and where a company should respond or engage in eWOM discussions are of key interest for marketing managers. Within the 28 papers identified in this section only two analyze possibilities for companies to moderate ongoing nWOM discussions. The majority of works, however, focuses on the importance of eWOM for viral marketing campaigns and try to answer the question of how companies can purposefully create eWOM (e.g., BERGER and MILKMAN, 2012). Furthermore, studies give advice on how social media can be implemented in corporate marketing strategies (e.g., VAN DER LANS et al., 2009, WINER, 2009). Even though there are plenty of articles with empirical backgrounds, the amount of theoretical contributions and game theoretical approaches is slightly dominating. This chapter follows the dual role of companies and presents results sorted by how companies can moderate ongoing eWOM discussions and how they can stimulate UGC through viral marketing campaigns. In one last stanza, the chapter at hand will present different views of how social media marketing beneficially ties into a company's overall marketing strategy.

The Company as Moderator. VAN LAER and DE RUYTER (2010) present results from three experimental studies with a main focus on corporate response strategies for nWOM communications on blogs. They investigate effects of response format (i.e., narrative vs. analytical), response content (i.e., denial vs. apology), and replying person (i.e., responsible employee vs. company's spokesperson) on the dependent variables of "intention to switch" and "perceived integrity". When a company chooses an analytical response format, consumers perceive greater integrity and switch less often if the response content is denial rather than apology. In case of a narrative response format, the integrity is higher and the intention to switch is lower if the response content is apology rather than denial. Consumers also perceive greater

integrity if the responsible employee, rather than a company's spokesperson issues the apology. To show empathy in a reply also turned out to be highly important. It, therefore, has a significant, positive impact on perceptions of the integrity of the accused party. Even though the authors created their scenarios only within the automobile, healthcare, and public railway context, they derive clear implications for practitioners. The approach of VAN LAER and DE RUYTER (2010) should be expanded to different industries and other settings to test the robustness of their empirical findings. The second study about effective means for companies to counteract nWOM was conducted by VAN NOORT and WILLEMSSEN (2012). They also use fictitious blog posts and apply a scenario of a car recall in the automotive industry. They focus on the role of webcare intervention strategies (i.e., proactive vs. reactive) and investigate the effects on "overall brand evaluation" moderated by platform type. The authors report that proactive intervention strategies engenders more positive brand evaluations on a brand-generated than consumer-generated platform. Further, they differentiate the perceived "corporateness" and "human voice" of a respective post. It is found that proactiveness is perceived as higher in natural human voice on a brand than consumer-generated platform. Reactive intervention strategies, however, create positive brand evaluations, irrespective of the platform and are also perceived as high in natural human voice. As the authors only look at one industry and provide scarce information about the experimental treatment, their approach has to be enhanced to other industries and settings. Also, a retrospective look at company engagements within archived nWOM discussions (e.g., on Facebook) seems promising.

The Company as Creator. Applying customer-leverage possibilities for corporate communication aspects has long been of interest for marketing managers (DE BRUYN and LILIEN, 2008, p. 151). Viral marketing can be seen as a technique which utilizes the internet to transmit and spread messages among individuals who will filter and forward the messages to their peers. The goal is to capture attention, triggering interest, and eventually cause product adoption or create sales (DE BRUYN and LILIEN, 2008, p. 152, WOERNDL et al., 2008, p. 34). By means of virally generated sales, higher revenues can be generated compared to traditional advertising efforts. VILLANUEVA et al. (2008) show that eWOM-induced customers add nearly twice as much long-term value to the respective firm. But it is still difficult to identify substantial evidence to explain why and how viral marketing works. This is why viral campaigns are currently viewed as more of an art than a science (DE BRUYN and LILIEN, 2008, p. 152). Articles in this section focus on the investigation of two major aspects of viral campaigns: Content deliberations and seeding strategies.

Content. The content is of crucial importance for viral marketing campaigns. BERGER and MILKMAN (2012) show that positive content is more viral than negative content. The authors add that marketing managers should target activating emotions (e.g., awe, anxiety, and anger) because they are linked to a higher virality. Emotions characterized by deactivation (e.g., sadness) are negatively linked to a campaigns success. Closely connected to these message characteristics, HO and DEMPSEY (2010) provide insight into what motivates people to process and forward online content. They report that a viral campaign is more successful when the communication strategy fits key motivations of the receivers. Opinion leaders' inclusion, altruism, and need for personal growth should be addressed to enhance virality of marketing messages. The content of a viral message has to further consider the current atmosphere within the target group (e.g., scandals/topics in society) to be successful. Furthermore, content should be humorous, creatively executed (BAMPO et al., 2008), have a high originality, and should create desire (LIN and HUANG, 2006). KOZINETS et al. (2010) conclude that blogs are highly suitable for viral campaigns. However, it has to be kept in mind that the content of viral messages has to fit in the system of character narratives, communication forms, and communal norms inherent on a respective platform. Importantly for marketers, the number of blogs about a product is also capable of predicting market outcomes (ONISHI and MANCHANDA, 2012). However, DROGE et al. (2010) add that only measuring the volume of positive mentions across blogs is too short. The posts and reactions following a viral message bear valuable information that should be extracted by the respective company for at least three days after the message was seeded on the specific blog.

Seeding. BAMPO et al. (2008) report that in general the reach is proportional to the number of seeds used. When resources allow contacting a high number of seeds, the structure of underlying networks is less important. But with limited resources, the network structure has a marked impact. The authors find that in particular, scale-free networks are efficient for viral campaigns. Thus, higher numbers of seeds can be exchanged trough identifying influential customers who might then function as hubs. Within their game theoretical study, GALEOTTI and GOYAL (2009) also report that knowing the underlying network structure is of crucial importance for viral campaign's success. However, they state that it is not always the most connected individual within a network that should be contacted at first hand. When a company wants to increase the strength of influence on each particular individual, it is the best option to target poorly connected individuals. HINZ et al. (2011) find that the highest number of referrals can be created if a message is sent to hubs or bridges of the underlying network. Hubs naturally have a multitude of connections. Bridges allow a viral message to spread across different

subpopulations of the network that would not be connected without them. It is also not always the most loyal customer who should be targeted. It has to be kept in mind that less loyal customers are more likely to attract less experienced and less informed people that are harder to reach for marketing managers (GODES and MAYZLIN, 2009). DE BRUYN and LILIEN (2008) add that given the importance of tie strength and perceptual affinity it is the network of friends and acquaintances rather than the network of professionals and colleagues that is most likely to generate awareness. However, not using very close social ties among the actors within the seeding process also proves inefficiency.

Besides the advice regarding viral content and seeding strategies, research also provides further insights about social media phenomena and marketing practice. In his theoretic contribution, KOZINETS (2002) introduces “Netnography” as a fast, simple, and cheap tool for marketing research. Highly relevant marketing information can be extracted much easier compared to the traditional method of ethnography by using brand communities and forums to conduct targeted marketing research. Research not only looks at the positive aspects of brand fan communities. KRISHNAMURTHY and KUCUK (2009) provide evidence that especially for successful brands with high brand value, the presence of anti-brand sites is a logical consequence. The number of anti-brand sites on the internet is directly associated with a decrease in brand value reported in the Business Week’s top 100 brand list of the years 2004 and 2005. However, CLEMONS et al. (2006) use data from eWOM discussions of a beer-rating platform in the USA to show that eWOM dispersion is positively associated with sales growth. It is thus more important to have some customers who love you than a huge number of customers who merely like you. Products targeted at consumers who tend to have extreme reactions will grow faster. To simply use eWOM as an external source of information is also not enough in today’s online environment. Companies also try to disguise corporate product ratings as UGC. In his game theoretic paper, DELLAROCAS (2006) finds that in a broad class of settings, firms of all types as well as society would be strictly better off if a manipulation of posts would not be possible. However, he adds that the current situation is similar to a “rat race”. Companies have to manipulate consumer generated eWOM messages to not suffer a strategic disadvantage.

How Social Media Ties into the Overall Marketing Strategy. Marketing by the directed activation of viral chains can be seen as more persistent compared to traditional advertising vehicles. TRUSOV et al. (2009) report that the effects of viral campaigns remain for approximately three weeks. Traditional tools of media and events wear off after just a few days. A similar effect on long term customer equity measures could be empirically shown by

VILLANUEVA et al. (2008). EWOM induced customers add twice as much long-term value to the firm than traditional marketing induced customers. Financial incentives should be used to boost the generation of eWOM and forwarding behavior. Following the argument of viral marketing's supremacy, many articles argue that social media marketing will substitute traditional vehicles because social networks are an unbiased milieu where peoples voluntarily and freely congregate and exchange information. Traditional push advertising itself is constantly losing credibility and impact (CLEMONS, 2009b, pp. 48, 52). In their game theoretical contribution, GALEOTTI and GOYAL (2009) show that for a firm with heavy advertising, eWOM and advertising are indeed substitutes. A boost in eWOM lowers optimal advertising spending and vice versa if a firm undertakes only little advertising to start with. MAYZLIN (2006) constrains the substitutional point of view in her game theoretical article and states that both can only be seen as equal when advertising messages are also anonymous. In her scenario, advertising messages are disguised as consumer generated eWOM messages and are, thus, indistinguishable to receiving consumers. However, on a market with inferior and superior products, this leads to the necessity for companies to spend more resources promoting inferior products. A unique equilibrium could be identified where eWOM is still a persuasive force regardless of promotional chat activities from competing firms. CHEN and XIE (2008) restrict the commutability of social media marketing and traditional advertising, too. They report that both are only substitutes when product costs are high and/or there are sufficient novice product users. In other words, a seller has to reduce advertising efforts after eWOM reviews become available. There is a complementary relationship when product costs are low and/or product users are more sophisticated. The sellers have to increase advertising expenditures when eWOM posts become available to combine eWOM and advertising effects for a superior outcome. By looking into data from an actual viral marketing campaign of a financial service provider, VAN DER LANS et al. (2009) found that marketing activities directly connected with a viral campaign show a stronger long-term effect. Targeted supportive advertising online and offline delays the wear-out effect of campaigns. Looking at blogs, ONISHI and MANCHANDA (2012) also conclude that both have a complementary relationship because pre-launch advertising spurs blogging activities but becomes less effective post-launch. An integration of viral marketing into existing marketing strategies as enhancer of traditional marketing seems to be the logical consequence due to its inexpensiveness and potential to quickly reach a large target audience. However, WINER (2009, p. 116) states that due to social media's interactivity and the sheer uncountable number of alternative ways to communicate with customers, the availability and integration of web 2.0 marketing opportunities has created both opportunities

and problems for managers and academics. Being “the new hybrid element of the promotional mix” (MANGOLD and FAULDS, 2009) and changing the marketing landscape to a “pinball like environment” (HENNIG-THURAU et al., 2010) exhibits the fact that customers and consumers have extremely strengthened their position in the web 2.0 environment. Only those companies who accept this new shift in powers and the necessary integration of new media into their marketing toolbox will survive the next 50 years (BREAZEALE, 2009, p. 313).

5 Conclusion, Limitations, and Implications

Appendices 1 – 4 provide a short evaluation of the studies used as input for the conducted narrative review. Nevertheless, some aspects of the selected studies shall be discussed in more detail. Overall, the quality of studies is rather high. Empirical analyses as well as theoretical contributions all show a superior level of quality that, of course, can be seen as a result of the article selection process described in chapter 3. Even though measurement techniques widely vary among the studies, they can be seen as consistently positive. Thus, criticism can only be made on a very high level, however, some general aspects regarding data bases, prevalent methods, and sampling characteristics have to be mentioned. With regard to eWOM effects on consumer mindset metrics, the majority of studies apply experimental setups mostly in laboratory settings. The use of mainly student samples as representatives of the general population may slightly bias the results regarding their different levels of income, education, age, and knowledge. Especially when taking into account that the average social media and network user for example in Germany is in his late thirties (BITKOM, 2011, p. 6)¹⁴. Social Media research needs subsequent field studies to investigate eWOM effects in real-life settings with a multitude of distracting information sources to judge the external validity of evinced results (cf. also LUO et al., 2013b, ARAL and WALKER, 2012). A challenging question for further research is also given by the endogeneity of eWOM discussions and its interconnection with previous performance measures as well as previous posting volume. Even though the narrative review at hand does not take inherent endogeneity into account, it provides a first framework for a classification of different eWOM research areas. I encourage further research to pick up the classification of my paper and conduct quantitative meta-analysis with a main focus on methodologies and data used to identify a quality label for major contributions in the field. Also, the focus of target journals for a quantitative approach should not only be limited to top-tier journals of the field but comprehensively collect contributions to the research stream. The multitude and highly diverse approaches, methodologies, and datasets, of course, make

¹⁴ This number is calculated on the basis of both private and professional social networks (e.g. XING).

quantitative meta-analysis a truly challenging task. But academics as well as researchers still strive to answer the question if the overall effect of social media is generalizable, stable, and comparable across studies conducted. Besides these methodological and sample aspects, the applied industries in the papers at hand also raise minor doubts about the generalization of the reported effects. A major part of studies applies eWOM and UGC data from the movie and book sector. This might be mainly for data availability reasons. However, the application of mostly experience goods in eWOM literature positively biases reported effects and has to be extended to other industries and product categories (e.g., service industry). Further, the conducted literature search was not limited to studies with a focus on eWOM created by consumers. It is interesting that only two studies could be identified with a focus on how companies can moderate negative consumer complaints and discussions. Strategies for counteracting negative consumer posts should be developed further to provide a broader toolbox for the social media responsible (e.g., MUNZEL and MEYER, 2011). The paper at hand also wants to encourage research to take the lack of eWOM escalation models as a starting point for further investigation. The question of what makes a negative post critical for brands is only partially answered (cf. e.g., DECKER and TRUSOV, 2010). The still blurred picture of valence and the strong influence of pure eWOM volume, so far, make it difficult to derive clear guidelines if and how valence of chatter and buzz shall be tracked for a superior monitoring of potential eWOM effects. It has to be considered if other classification schemes of UGC might be more efficient than a pure separation in positive, neutral, and negative chatter. Beyond that, social media platforms like Facebook or Google+ are underrepresented in today's top tier journals. Whereas plenty of research is available supporting practitioners within viral marketing campaigns, little is known about the right application, design, or posting activity of companies on corporate or brand fan pages, even though similarities to viral campaigns can be observed (cf. e.g., JAHN and KUNZ, 2011, p. 105). Practitioners seem to follow a trial-and-error strategy on their brand pages mostly guided by simple reach metrics as number of likes or number of comments (cf. e.g., DE VRIES et al., 2012). Research has to extend these awareness-like metrics and investigate if and how it is possible to move consumers further down the brand funnel. Questions like "are targeted company-generated posts on e.g., Facebook able to strengthen a consumer's attitude towards a brand, purchase intention, or brand image" have to be put on research agendas. In addition, brand image effects of eWOM have not been investigated in any study of the sample at hand.

This paper provides a road map for practitioners showing effects of social media metrics on corporate performance measures along the value chain. The integration of social media and

especially eWOM marketing can be seen as an elementary requirement of web 2.0 developments as traditional push marketing will become more and more limited (KOZINETS et al., 2010, p. 87, CLEMONS, 2009b, p. 55). The interactive involvement of the customer and a constant engagement in social media communications is unavoidable (HENNIG-THURAU et al., 2010, p. 324). This does not mean that companies only have to produce content in a creative, humorous, and original way to entertain customers, users, or fans (BAMPO et al., 2008, LIN and HUANG, 2006). It also means to be informed about a company's current temperature in the web 2.0 environment. This paper shows that eWOM volume measures already enable a prediction of subsequent effects along the social media value chain. It becomes obvious that discussions on the internet indeed influence key firm performance metrics. A regular tracking of key social media metrics like level/volume of chatter and buzz with a parallel valence coding is a key issue for today's marketers. Even though there are some tendencies that information given within UGC posts is not completely processed by consumers, a pure extraction of simple rating measures would fall short. IT-coded valence algorithms are a cost effective alternative to hand-coding, but flaws in language processing algorithms have to be kept in mind. Firms should further implement social media metrics into early warning systems and marketing dashboards. By doing so, companies are able to use the real-time communication of web 2.0 to their advantage, be up-to-date, and able to counteract negative developments immediately. Defining guidelines of how to answer and handle negative consumer posts on social media platforms is also a key success factor. Taking into account that corporate social media actions again form a touch-point with customers, which itself is again an important antecedent for eWOM creation, also fosters high relevancy for marketers today. A good management of UGC as well as a good communications strategy for brand pages does not necessarily boost firm performance measures right away. However, it provides a base for a constant positive development of a company or brand and forms an important precursor for consumer mindset metrics and corporate performance measures.

Appendix 1 – 4

Appendix 1: Overview of Studies - eWOM and Consumer Mindset

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
ADJEI et al. (2009)	Brand community/discussion forums (company hosted and one independent); Two forums of woodworking equipment 212 threads with 636 distinct posts (04 – 11/2004)	eWOM data (Relevance, valence (subjective), volume, Length)	Uncertainty reduction; Customer purchase behavior	Platform type; Expertise, Product complexity; Valence	Survey; Experiment; Netnography; SEM
	Main Results	Communication quality: reduces uncertainty about the firm and its products; Company/externally hosted: no significant difference - both show significant, positive effect on purchase behavior; Valence of information: positive information enhances the influence of uncertainty reduction and purchase behavior; Product complexity: positively moderates the effect on uncertainty reduction; Perceived respondent expertise: positively moderates the effect on uncertainty reduction			
	Limitations	Neglect of the potential impact of other factors on uncertainty reduction and on the quality of the relationship			
AGGARWAL and SINGH (2013)	Data from VentureXpert database (n = 33). Venture capitalists shared their deal flow data of the year 2008. Blog data stems from a blog search engine. Empirical analysis how eWOM influence the decision making process of venture capitalists	eWOM data/blog data (volume, valence (IT-coded))	Decision making stages (i.e., screening, choice, and contract stage); Level of interest		Regression
	Main Results	Volume of blog coverage increases the probability with which an entity will pass the screening stage of a venture capitalist but not their choice stage decisions; After the screening stage, blogs are non-influential since decision makers evaluate entities closely at later stages; However, blogs increase the interest from multiple decision makers which in turn increases the cost of the deal for a venture capitalist as the decision maker			
	Limitations	No nWOM considered - only pWOM included			
ALJUKHADAR et al. (2010)	Online experiment (n = 423) using a realistic website representing the e-store of a fictitious retailer; Manipulation of privacy disclosure using “Media Richness Theory”	Media richness of privacy disclosure presentation on retailers websites	Retailer trust; Purchase intention	E-store social presence; Agent trust; Perceived risk	Experiment; SEM
	Main Results	Social presence of e-store: directly affects retailer trust and purchase intentions; Mediating role between media richness and retailer trust; Retailer trust: positively influences purchase intentions through attenuating the level of perceived risk			
	Limitations	Only subjective self assessment of constructs within experiment			

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
BENLIAN et al. (2012)	Experimental setup that analyzes the differential effects of provider reviews vs. customer reviews on consumers' decision outcomes. N = 396 participants were recruited for a shopping task on a fictitious Amazon shopping website for a search and experience product (calculator vs. CD)	eWOM source manipulated (UGC vs. provider generated content)	Reuse intention of eWOM source; Purchase intention	Product type: search vs. experience goods	Experiment
	Main Results	Not all eWOM types are equally conducive in influencing trusting beliefs, perceived affective quality, and perceived usefulness; UGC was found to be superior to provider WOM in influencing consumers' trusting and affective beliefs, while provider information was found to have stronger effects on instrumental consumer beliefs. UGC provide more useful, trustworthy, and higher quality information whereas provider recommendations are perceived to be more useful and are superior in terms of their ease of use; Both can drive purchase intention but it has to be consistent with the communicated values of a specific product			
	Limitations	No longitudinal data			
BART et al. (2005)	25 websites from eight industries; 6,831 usable responses	Website characteristics	Online trust; Behavioral intent	Consumer characteristics; Trust	SEM
	Main Results	Website characteristics: influence differs significantly for website categories; privacy + order fulfillment greatest influence on trust for web sites with high informational risk and involvement; Navigation most important for information-intensive sites; Advice most powerful determinant for search goods; Consumer characteristics: influence on trust and behavioral intent differs significantly for customer groups; higher educated: online trust leads to a greater influence of brand strength on online trust levels and partially mediates the relationships between website/consumer characteristics and behavioral intent			
	Limitations	Only cross-sectional view; no interaction effects were looked at; only reflective construction of constructs			
BICKART and SCHINDLER (2001)	Online experiment (n = 61 students) comparing UGC (discussion forum) and CGC (corporate website) as information source about a product category (cycling, exercise, nutrition, photography, or stereo equipment)	Source of information (UGC vs. CGC)	Purchase likelihood; Knowledge, thought and interest in product category	Gender	Experiment
	Main Results	UGC vs. CGC: UGC creates more product category interest than CGC; Effect higher for female participants; No effect on amount of knowledge or thought			
	Limitations	Small sample size; Student sample			
BRODIE et al. (2011)	Literature analysis and netnographic methodology to define "consumer engagement" in a virtual brand community and to explore the consequences of consumer engagement, 427 posts of Vibra-Train Ltd. Online platform (Whole body vibration) from 11/2006 to 03/2008	Consumer engagement (closely related to eWOM volume and valence)	Consumer loyalty; Satisfaction; Empowerment; Connection; Emotional bonding; Trust, Commitment		Netnography
	Main Results	High consumer engagement: higher consumer loyalty, satisfaction, empowerment, connection, emotional bonding, trust, commitment; Marketers: are only accepted when they contribute to discussions; Should listen to and engage in communities which are perceived as non-commercial			
	Limitations	Only one small community with only six major users without any empirical validation			

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
CHAKRAVARTY et al. (2010)	Three experimental studies about movie eWOM (n = 157/128/119 students); Two with simulated website that mimics Yahoo! Movies board and one with print copies of website with eWOM and contradictory critics reviews	eWOM data (valence); Critics movie reviews/ratings (valence)	Pre-release movie evaluation	Movie going frequency	Experiment
	Main Results	Movie going frequency: higher influence of eWOM on infrequent moviegoers than on frequent moviegoers; Stronger for nWOM than pWOM; Critics movie rating: contradictory critical rating attenuates the effect of eWOM in case of pWOM (and negative critics rating); no attenuation effect when nWOM (and critics rating is positive); Contradictory critics reviews influence frequent (infrequent) moviegoers' evaluation of the movie more (less) than contradictory eWOM			
	Limitations	Only single item assessment of movie evaluation but multi dimensions were faced within critics reviews			
DE VALCK et al. (2009)	Online recipe/cooking orientated community; Recipe exchange between members (n = 1,007); Identification of user types	Community interaction characteristics	Decision making process	Internet proficiency; Membership characteristics	Cluster Analysis; Regression; Netnography
	Main Results	Frequency of community visit: positive effect across all decision making phases; Retrieval of information: positive effect across all decision making phases (except need recognition); Different membership types identified: core members, conversationalists, informationalists, hobbyists, functionalists, opportunists			
	Limitations	Self reports are base for clustering members and identifying influences on decision making phase, cooking forum not representative			
DEWAN and RAMAPRASAD (2012)	Empirical analysis how music discovery through social media influences music sales (approximated by music sampling). Data from TheHypeMachine (tool that tracks music posts from blogs) of 281 blogs posting from 07/2006 – 08/2006, Amazon (review data and sales ranks), and Nielson SoundScan of a total n = 1,762 albums	eWOM data (volume, valence (ratings), blog popularity/visibility)	Product choice/ consumption of music sampling; Sales	Product type: Niche product vs. mainstream	Regression
	Main Results	eWOM volume has an influence on music sales; Blog popularity has a stronger association with music sampling in the case of niche compared with mainstream music albums; The more popular or visible a music blog is, the higher its effect on music sampling; New social media in the form of music blogs are exposing consumers to a wider range of music than traditional media such as the radio; Music blog sampling is associated with higher song sales for both categories			
	Limitations	Sampling data collected only at a single point in time; Only one online music community analyzed			
DE BRUYN and LILLEN (2008)	Experimental study simulating a viral marketing campaign by inviting to an online survey; 634 students as initiators of email chains	Viral eWOM messages (eWOM volume)	Awareness; Interest; Product adoption	Tie strength/ perceptual affinity; Demographical similarity	Experiment
	Main Results	Viral eWOM: is able to create awareness, interest and product adoption; Source differences: the stronger the tie, the more likely to create awareness; Perceptual affinity is positively related to likelihood of generating interest; The greater the demographical dissimilarity between sender and receiver, the more likely to generate awareness, interest, and product adoption			
	Limitations	The experimental survey setup is only a weak indicator for product adoption, omission of relevant recipient-side independent variables			

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
DECKER and TRUSOV (2010)	Over 20,000 online product reviews (statements and product ratings) for major 4 cell phone brands in Germany (high-involvement); Natural language processing techniques (and human coders for validation)	eWOM data (volume, valence)	Overall valence of products discussed in online forums (rating)	None	Regressions; Adaptive conjoint analysis for validation
	Main Results	Product attributes influence: reliability and quality topics discussed in online reviews have highest impact on consumer preferences; provides list of discussion topics and quantifies influence on preferences; Binominal regression: good predictive accuracy to extract consumer preferences from eWOM data on the internet			
	Limitations	No consideration of self-selection within eWOM data			
GARNEFELD et al. (2010)	Two experimental studies (n = 168/342 students) to test the loyalty effect on eWOM senders; Cell phone service provider; On- and offline situations	eWOM referral programs	Loyalty; Affective commitment	Product expertise; Experience with brand	Experiment; SEM
	Main Results	Articulating eWOM: enhances senders affective commitment; stronger effect on affective commitment for inexperienced- and low level of experience communicators; Positive effect on sender's behavioral loyalty (partially mediated by affective commitment)			
	Limitations	Only two moderating variables are considered, loyalty and commitment as long-term constructs may be difficult to manipulate in an experiment			
GRUEN et al. (2006)	Survey in a company independent internet forum of a popular software product for video editing (n = 616)	C2C know-how exchange	Loyalty (repurchase and WOM); Overall value of the firms offering	None	Online survey; SEM
	Main Results	C2C know how exchange: positive effect on perceived value of the firms offerings; positive effect on WOM (direct and indirect through perceived value); Positive effect on repurchase (only indirect through perceived value)			
	Limitations	Limited measures of behavioral constructs; Consideration of a cross-sectional snapshot of a point in time, but the phenomenon builds over time			
GUPTA and HARRIS (2010)	Laboratory experiment; Purchase of a laptop computer in a realistic online retail setting as experience good (n = 198 students); Variation of the eWOM and laptop on which the eWOM was provided	Manipulated eWOM data (volume)	Choice optimality; Total time spent on site; Time spent considering the eWOM	Need for cognition (NFC)	Laboratory Experiment
	Main Results	eWOM: eWOM message increases total time on decision tasks; causes higher time evaluating the product suggested through eWOM; Need for cognition: high NFC increases total time spent on decision tasks; Under a lower NFC condition, people reduce their decision optimality based on the presented eWOM; under a high NFC condition, people only follow eWOM recommendations when it is the optimal product; High NFC consumers are willing to move away from stated preferences to eWOM recommendations			
	Limitations	No consideration of nWOM; Focus on only one product category (laptops); External validity restricted due to the student sample; No real shopping conditions			

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
JANG et al. (2008)	Online survey of 250 online community members of mobile phone brands, consumer electronics, and automotive	Characteristics of online brand communities	Brand loyalty; Community commitment	Community type	Regression
	Main Results	Community interaction/reward: both positively related to brand community commitment; Community types: information quality and system quality is more related to community commitment in consumer-initiated communities; Brand community commitment: positively influences brand loyalty			
	Limitations	Critical sample issues, questionnaire very superficial			
JIMÉNEZ and MENDOZA (2013)	First laboratory experiment (n = 201 students) using a search product (i.e., cell phone) and artificially designed consumer reviews with different levels of detail. The second online experiment (n = 83 students) uses an experience product (i.e., hotel) – both using scenarios and no real life setting	eWOM data (fictitious eWOM messages with different levels of information detail, reviewer agreement/variance)	Purchase intention; Review credibility	Product type: search vs. experience goods	Experiment
	Main Results	Level of eWOM detail shows a positive effect on purchase intention in case of the search product – no effect was found in case of the experience product; The effect is fully mediated by the perceived review (source) credibility; The reviewer agreement (variance) has a direct positive effect on purchase intention of search and experience products			
	Limitations	No realistic manipulation of other review criteria beside level of detail as aspect like product price, ratings, source, length, and valence were controlled			
LI (2010)	Game theoretical model about incentives to contribute to online auction markets' feedback mechanism in a truthful manner; Reputation systems from a seller and buyer perspective using the case of eBay	No empirical data; Tackles concerns of buyers in online auctions to give truthful feedback for behavior of seller because of the fear of retaliation			Game theoretic model
	Main Results	Giving sellers the option to compensate buyers for reporting eWOM can solve the problem of untruthful eWOM contributions and pWOM bias; Rebates for buyers could also lead to a better possibility of distinguishing between good and bad sellers and, of course, higher eWOM volume; Suitable rebate systems could be a combination of automatic feedback for buyer's behavior and monetary incentives or community recognition			
	Limitations	No empirical validation of conceptual model			
NAMBIAN and WATT (2011)	Product community data of IBM, Adobe, Intel, and Microsoft to assess how companies can manage consumer experiences in online product forums; Web-based questionnaire (n = 178)	Online community experience; Pragmatic, hedonic, sociability and usability dimension	Attitude towards the product/company; Perceived service quality	None	Regression
	Main Results	Online community experience: positively related with attitude towards the product over all dimensions; Positively related with attitude towards the product and perceived service quality for pragmatic, hedonic, and sociability dimension			
	Limitations	Only technology-based product category was examined; Primary role of online product communities in the sample was to serve as a vehicle for delivering product support services to customers			

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
NARAYAN et al. (2011)	Empirical study of electronic book reader choices (n = 70 students) and cell phone choices (n = 140 students); The power of peer groups to update and shape individual preferences	Social network membership, Frequency of peer interaction (eWOM volume and valence)	Choice of electronic book readers; Choice of cell phones	Social network peer group; Influencing power of individual peers; Demographics of peer recommenders	Bayesian model; Choice-based conjoint study
	Main Results	Consumers' weight on own preferences diminishes with increasing number of peer influencers; Preference change due to peer influence depends on consumer's uncertainty about the importance of a certain product attribute; Consumer's preference revision will be more likely when contacting an additional consumer for the first time than re-contacting a consumer; Social network data (also internet based) can be used as solid proxy for sociometric measurements that model social relationships and interactions			
	Limitations	No representative sample and study does not consider WOM messages that are not related to product attributes and choices			
PAN and CHIOU (2011)	Fictive messages on artificial discussion board; Social relationships between sender and receiver and experience (hotel services) vs. credence goods (health foods) were looked at (n = 284 students)	eWOM data (valence)	Perceived trust-worthiness of messages; Overall attitude towards the product	Relationship between sender and receiver; Experience vs. credence goods	Experiment; SEM
	Main Results	pWOM (nWOM) is positively (negatively) related with attitude towards the product; Perceived trustworthiness: positive effect on attitude towards the product; Social relationship: pWOM and nWOM perceived as credible for experience goods as long as author has close social relationship; nWOM perceived as more credible than pWOM for credence goods when author has close social relationship; Product type: negative messages are seen as more trustworthy than positive messages in the case of experience goods; Effect of information trust on attitude is weaker in the credence goods group than in the experience goods group			
	Limitations	Doubtful manipulation of social relationship by message wording; Personal knowledge and prior attitudes of participants were neglected			
PARK and LEE (2009)	Experimental questionnaire setup (n = 440) with 55 respondents in each treatment condition; One established online retailer and one made up	eWOM data (manipulated)(valence, Website reputation)	eWOM effect (3 items); Purchase decision	Product type: search vs. experience goods; Website reputation	Experiment
	Main Results	eWOM valence: the purchase influence of nWOM is greater than for pWOM; Product type: Negativity effect of nWOM appears to be stronger for experience goods than for search goods; The eWOM effect is greater for experience goods than for search goods; Website reputation: eWOM effect is greater for established websites than for unestablished – source credibility; Product type/website reputation: the eWOM effect difference of established and unestablished websites is greater for experience than for search goods			
	Limitations	Focus on product-related eWOM; No consideration of consumer characteristics (e.g., involvement, commitment towards the product/brand)			
PARK et al. (2007)	A virtual shopping mall site using a portable multimedia player as product of interest formed the experimental setup together with artificial pWOM product reviews (n = 352 students)	eWOM data (pWOM, volume, Quality)	Purchase intention	Product involvement	Experiment
	Main Results	pWOM quality and volume: positively affect consumers' purchasing intention; Product involvement: low-involvement consumers are affected by the quantity rather than the quality of reviews; High-involvement consumers are affected by review quantity mainly when the review quality is high			
	Limitations	Negative reviews and mixed-quality reviews were neglected; Personal knowledge and prior attitudes of participants were neglected			

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
PARRY et al. (2012)	Online questionnaire with early Japanese adopters of cell phones (n = 603) and Bluray DVD recorder (n = 610). Data collected in March 2010. Studies focuses on the comparison between virtual WOM and eWOM	eWOM (scale adapted from PARK and LEE (2009))	Perceived usefulness; Perceived ease of use; Purchase intention	Social and symbolic visibility of consumption	SEM
	Main Results	For both product categories, personal as well as eWOM are positively associated to the ease of use dimension of the product. In both product categories, personal WOM is positively and significantly related with perceived usefulness, while eWOM is significantly related with perceived usefulness only in the smart phone sample. Both, perceived usefulness and ease of use subsequently show a strong positive prediction for purchase intent. The Bluray recorder segment shows higher purchase intent than the smart phone sample			
	Limitations	No longitudinal data; Online questionnaire leads to an online biased sample			
SCARPI (2010)	Online questionnaire within online communities of roses' enthusiasts (n = 750), 60% of participants from three large communities and 40% from five minor ones	Community identification	Brand loyalty; Community loyalty; Brand affect	Brand community size	SEM
	Main Results	Community identification: positively influences brand affect and community loyalty; Brand affect: positively influences brand loyalty; Community loyalty: positively influences brand loyalty, brand WOM, and community WOM; Impacts community WOM more than brand WOM; Brand community size: the relationship between community identification and community loyalty, between community loyalty and brand loyalty, and between community loyalty and community WOM is stronger in small communities than in large communities; The relationship between brand affect and brand loyalty is stronger in large communities			
	Limitations	Narrow set of online communities of only one specific industry			
SEN and LERMAN (2007)	Observation study and two laboratory experiments (n = 137/120 students); Consumer reviews on e-retailer website adapted for fictive products; Five utilitarian and hedonic (i.e., PDAs and movie) products	eWOM data (valence, Helpfulness)	Attitude about the product; Perceived usefulness of the review; Attribution	Product type (utilitarian vs. hedonic)	Experiments
	Main Results	eWOM valence: positively influences the attitude towards the product, negativity bias for utilitarian product reviews only; Product type: moderates the effect of review valence; readers engage more with nWOM than pWOM in the case of hedonic products; nWOM in the utilitarian case, readers' are more likely to attribute nWOM to product related motivations; nWOM in hedonic reviews is more likely to be attributed to the reviewer's internal/personal reasons			
	Limitations	Manipulation of hedonic versus utilitarian products by using two different products, though in the same product category			
SENECAL and NANTEL (2004)	Experiment with product recommendations for search (calculator) and experience (wine) goods; n = 630 in the survey and n = 487 in the survey and the experiment	Types of recommendations (other consumers, recommendations system, and human experts)	Consumer choice behavior	Product type; Website type; Source trustworthiness; Perceived expertise	Online Questionnaire; Experiment
	Main Results	Recommendation systems: consumers who consult a recommendation are more likely to select the recommended product; recommender systems are more influential than other consumers and human experts; Product type: consumers more influenced by recommendations for experience than for search products; Website type: no significant influence; Source trustworthiness: source "other consumers" more trustworthy than "recommender system"; Source "other consumers" as trustworthy as "human experts"; Perceived expertise: "other consumers" are perceived as less expert than "human experts" and "recommender systems"			
	Limitations	Sample not representative of the population of internet shoppers; Only one experience good (wine) and one search good (calculator) observed			

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
SMITH et al. (2005)	Two experimental studies (n = 252/150 students) with a hedonic and utilitarian scenario; Fake restaurant guide website with different eWOM types	Peer recommendations; Editorial recommendations	Decision-making process; Product choice	Shopping goal; Expertise of sender; Rapport with the recommender; Trust	Experiment
	Main Results	Trust in peer recommender: the greater trust, the greater the perceived influence; Expertise of peer recommender: the greater the expertise of a peer recommender, the greater the perceived trust of the recommender and the greater the perceived influence; Rapport with peer recommender: the stronger the rapport with a peer recommender, the greater the perceived trust of the recommender and the greater the perceived influence; Rapport and expertise: the higher expertise and rapport, the greater preference for peer relative to editorial recommendation; Shopping goal: the more utilitarian, the stronger the impact of expertise, the more hedonic, the stronger the impact of rapport and the greater the preference for using peer recommendation relative to editorial recommendation			
	Limitations	Focus on only one product category (restaurants); Only positive recommendations; Variation of the quantity of information in the peer versus the editorial recommendations			
THOMPSON and SINHA (2008)	Four brand communities (x86 microprocessors (Intel and AMD); 3D video cards (ATI and NVIDIA) and 2 general forums; 27,777 user accounts with 990,818 messages	Forum posts (eWOM volume and valence); Forum overlap; Total posts; Posts per day	Product adoption (competing and preferred brand)	None	Hazard models (linear regression)
	Main Results	Higher brand community participation: higher brand loyal adoption behavior and less time of adoption, less likely to adopt a product from a competitor; Membership duration has the same effects; Overlapping community memberships across rival brand communities can actually reverse these relationships			
	Limitations	Product category with low visibility might influence community members behavior			
THORBJØRNSEN et al. (2002)	Experimental study (n = 123 students) of personalized Web sites and customer communities; Comparison for their ability to develop consumer-brand relationships; Two fictive websites of airline tickets and restaurant-meals	Type of interaction on website (i.e., personalized web site vs. customer community)	Brand relationship quality	Internet experience	Experiment; SEM
	Main Results	No main effect of internet application (i.e., personalized web site and customer community) on brand relationship quality was found; Internet experience: customer communities (person interactivity) more effective than personalized web sites (machine interactivity) in building brand relationship quality when consumer internet experience was low; Personalized web sites were more effective than the customer community sites when internet experience was high; The single dimensions of the measure brand relationship quality do not significantly differ between personalized websites and brand communities			
	Limitations	Ten day experimental set up too short for establishing a brand relationship with a fictive brand			
WANG et al. (2012)	Online questionnaire conducted in 12/2010 of n = 292 social media users of the platforms QQPengyou, Renren.com, Kaixin.com, 51.com, or other sites	eWOM (only positive discussions)	Attitude toward the product; Purchase intention	Need for Uniqueness	SEM
	Main Results	eWOM interactions on social media platforms affected product attitudes, which in turn enhanced purchase intentions; Tie strength with peers and group identification with peer group form antecedents of successful peer interaction; Product involvement mediates the relationship between peer communication and attitude toward the product; The effect of peer communication on attitude appeared more evident for consumers who scored low in their need for uniqueness			
	Limitations	Only Chinese social media sites included; Only pWOM considered			

Appendix 2: Overview of Studies - eWOM and Product and Market Performance

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
AMBLEE and BUI (2008)	Consumer reviews of 395 Amazon 49-cent e-books in PDF format sold from 06/2006 until 12/2006; Results from logistic regression are confirmed by time series regression	Brand Reputation; Complementary goods' reputation	eWOM volume, Sales rank for the interrupted time series model		Logistic Regression, Interrupted Time Series
	Main Results	eWOM volume: significant effect on future sales			
	Limitations	Operationalization of reputation by average authors scores on consumer review platform remains critical; EWOM valence was not looked at on aggregated level; Only e-books were looked at without any controls for advertising etc.; Paper focuses how eWOM is influenced and only marginally takes eWOM as exogenous			
ANDERSON and MAGRUDER (2012)	Dataset with average star ratings gather from Yelp.com (i.e., restaurant review website) for restaurants in San Francisco, CA up to 02/2011 (n = 3,953 restaurants). Restaurant reservation data collected from a large online reservation website from 07/2010 to 10/2010 (n = 328 restaurants with reservation data)	eWOM data (volume, valence (ratings) per review and average)	Offline sales (restaurant reservation capacity)		Regression discontinuity design
	Main Results	An extra half-star rating in eWOM causes restaurants to sell out 19 percentage points (49%) more frequently, with larger impacts when alternate information is more scarce; These returns suggest that restaurateurs face incentives to leave fake reviews but a rich set of robustness checks confirm that restaurants do not manipulate ratings in a confounding, discontinuous manner; eWOM provides a convenient forum for solving asymmetric information problems			
	Limitations	No information about how reservation data transfers into monetary equivalents for the restaurants			
CHEN et al. (2004)	Consumer book reviews/ratings and algorithm based recommendations from Amazon.com; Book reviews of 610 books from December 2003	eWOM data (volume, valence (ratings)); Recommendation volume	Online sales ranks		Regression
	Main Results	Volume/valence: volume positively associated with higher sales, valence not related to sales; Product recommendations: positively related to higher sales but not for popular books			
	Limitations	Focus on only one product category (books); Consideration of only one web site (Amazon.com), may not be representative			
CHEN et al. (2011b)	Consumer digital camera reviews and observational learning (OL) data (automated product recommendations) from Amazon.com; 90 digital cameras from 09/2005 – 03/2007	eWOM data (volume, valence (ratings)); OL data (Purchase probability, Positive (listed) and negative)	Online sales ranks		Natural experiment
	Main Results	nWOM: significant effect on sales; nWOM and pWOM of ratings: nWOM higher effect on sales than pWOM (in study 2 even not significant); OL: positive information shows positive sales effect; WOM and OL: diminishing effect over the product lifetime; positive complementary effect between OL and volume			
	Limitations	Relatively small sample size and only one product category (digital cameras) and web site (Amazon.com) were analyzed			

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
CHEVALIER and MAYZLIN (2006)	Consumer book reviews/ratings from Amazon.com and Barnesandnoble.com; 2,387 books in 05/2003; 2,082 books in 08/2003 and 1,636 books in 05/2004	eWOM data (volume, Review length, valence (ratings))	Online sales ranks	Price	Regression
	Main Results	Amazon vs. Barnesandnoble: sales ranks respond more to prices at Barnesandnoble; Sales differences across the two websites related to differences in ratings; pWOM and nWOM: influences consumer purchasing behavior; nWOM is more effective than pWOM; Review length: does not necessarily stimulate sales			
	Limitations	No consideration of the review generating process, response to reviews may increase or decrease their degree of information; Focus on only one product category (books)			
CHINTAGUNTA et al. (2010)	Consumer movie reviews from Yahoo! Movies; 148 movies from 11/2003 to 02/2005 sequentially released in the USA	eWOM data (volume, valence (ratings), Variance)	Offline box office ticket sales data		Panel regression
	Main Results	Valence: significant positive effect on opening earnings and box office performance; Volume and variance: no significant impact on future box office performance; Aggregation of eWOM data: diminishes the effect of valence and increases volume measures			
	Limitations	Neglect of the potential impact of other sources of consumer generated media (e.g., blogs, online discussion boards); Focus on only one product category (movies); Consideration of only one web site (Yahoo! Movies), may not be representative			
DELLAROCAS et al. (2007)	Consumer movie reviews from Yahoo! Movies, BoxOfficeMojo and Hollywood Reporter; 80 movies released in 2002; 55,156 reviews in total from 34,893 users	eWOM data (volume, valence (ratings), Gender entropy of sender)	Box office revenue during opening week		Diffusion model
	Main Results	Volume: proxy of early sales; Valence: predicts future eWOM volume and predicts publicity of movie in general; Gender entropy of reviewers: helps to predict initial appeal as well as eWOM influence from previous moviegoers on future sales			
	Limitations	Neglect of potential impact of competing movies and only one product category (movies) is investigated			
DHAR and CHANG (2009)	Volume of blog chatter (Technorati), eWOM and social network connectivity before and after the release of 108 music albums in the USA between January and March 2007	Blog chatter eWOM data (volume, valence (ratings), Artist's friends on MySpace)	Online album sales rank	Volume of traditional reviews; Volume and valence of media reviews	Panel regression
	Main Results	Social network connectivity: no predictive power; Valence of online reviews: predicts sales one week ahead; Volume of blog posts: predicts sales one and two weeks ahead; Traditional reviews: predicts sales one, two, and three weeks ahead			
	Limitations	Blog post valence not considered as well as prior track record of the artists; Focus on only one product category (music albums)			
DUAN et al. (2008a)	Consumer movie reviews from Yahoo! Movies; 71 movies released in the USA between July 2003 and May 2004	eWOM data (volume (cumulative and daily), User ID, Date/time, valence)	Offline box office revenues; Sales rank; Theater revenue		Panel regression
	Main Results	eWOM valence: no significant effect on sales in opening week; Daily eWOM volume: positively predicts box office revenues in week one and an even stronger impact on sales in week two, predicts tomorrow's eWOM volume; Decreases when previous reviews already provide enough information (high previous cumulative volume); Previous day's sales predict today's box office revenues, positively drives eWOM volume			
	Limitations	No consideration of pre-release WOM; Focus on only one product category (movies) and one website; Restriction of the sample to online users who choose to post reviews and post them on Yahoo! Movies			

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
DUAN et al. (2008b)	<i>Same data and set up like DUAN et al. (2008a) but including lagged independent variables</i>				
	Main Results	eWOM volume: significantly predicts daily box office revenues; significantly predicts movie sales beyond the concurrent term - however, the influence diminishes quickly; Movie sales: influences concurrent eWOM volume, influences eWOM volume beyond the concurrent term - however, the influence diminishes quickly; eWOM valence: positively influences eWOM volume			
	Limitations	See above			
ETZION and AWAD (2007)	Consumer electronics reviews from a large online retailer; Products of 6 major categories of consumer electronics were screened between April 1999 and March 2005	eWOM data (volume, valence (ratings))	Online sales		Regression
	Main Results	Volume vs. valence: increase in volume is associated with an increase (decrease) in sales when valence is above (below) an anchor point; When valence already provides differentiation possibilities volume not needed for choices; Valence: increase in valence related to an increase in sales; Increase in average valence for competing products related to a decrease in sales; Volume: only has significant (negative) effect, when product valence is close to the subcategory average			
	Limitations	No consideration of the impact of competing retailers; focus on only one product category (electronic products)			
FORMAN et al. (2008)	Consumer book reviews from Amazon.com (reviewer disclosure information and ratings); 786 books from all categories between 04/2005 and 01/2006 with a total of 175,714 reviews	eWOM data (volume, valence (ratings), Helpfulness); Reviewer data (name, location/disclosure)	Online sales rank	Geographic proximity of reviewer and receiver; Reviewer information disclosure	Panel regression
	Main Results	Reviewer information disclosure: positively related with both perceived helpfulness and sales, this link is even enhanced through geographic proximity of reviewer and receiver; Reviews of reviewers with disclosed information are rated more positively; eWOM valence: no significant effect on sales when reviewer information is disclosed; but nationwide aggregated eWOM valence is still positively related to regional sales			
	Limitations	No direct measure of the level of Amazon member identification; No consideration of changes in product popularity; Valence and quality of the review text not considered; Focus on only one product category (books); Consideration of only one web site may not be representative			
GODES and MAYZLIN (2004)	Consumer reviews from 20 Usenet newsgroups of new TV shows; 44 TV shows 1999-2000 with a total of 2,398 posts	eWOM data (volume, valence (hand coded), Length, Dispersion)	Offline sales (TV viewership rating)		Panel regression
	Main Results	Dispersion of eWOM: positively related with higher TV ratings, impact of dispersion declines over time; Volume vs. dispersion: dispersion more important than volume; Volume of eWOM: only shows positive influence in the later periods of TV shows lifecycle; In early stages of TV show lifecycle, no significant effect negative and positive volumes may have offsetting relationships with future ratings; Valence of eWOM: no effect; Higher viewership: leads to higher eWOM			
	Limitations	Focus on only one product category (TV shows); No consideration of other factors (e.g., advertising) that may have influenced WOM or TV ratings			

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
GODES and MAYZLIN (2009)	Field study for two eWOM creator subpopulations: customers of a restaurant chain (Rock Bottom Brewery; n = 381) or independent eWOM creators from a marketing agency (BzzAgent n = 692) 04/2003 – 06/2003; Experimental study with n = 96 college students confirming the results	CGC vs. eWOM (Source (customer vs. non-customer))	Offline firm sales; Number of WOM episodes reported	Loyalty of sender; Opinion leadership; Product awareness	Panel regression; Experiment
	Main Results	The sales impact of eWOM from a less loyal customer is higher than that from a loyal customer; The sales impact of eWOM to an acquaintance is higher than that to either a friend or a relative; Less-loyal customers should be recruited in a company induced eWOM campaign; Opinion leadership is associated with the creation of more eWOM for loyal customers, however, less true for less-loyal customers; For products with low initial level of awareness, loyal customers are not necessarily the cornerstone of a successful eWOM campaign			
	Limitations	Difficulties to control for all the differences between the customer and the non-customer populations			
GU et al. (2011)	Consumer reviews for digital cameras (high involvement good) from Amazon, Cnet, DpReview, and Epinions; 148 models in a price range from \$100 to \$5,000	eWOM data (volume, valence (ratings))	Online sales rank Amazon	eWOM source – internal (from Amazon) or external	Panel regression
	Main Results	Volume and valence: significant effect on high-involvement product sales for internal and external eWOM; Internal vs. external eWOM: external eWOM (valence and volume) has more influence on internal camera sales than internal eWOM; External WOM sources: are likely used within high-involvement decisions			
	Limitations	Study limited to well-known products (Canon, Nikon); No consideration of information search behavior; No analysis of the information content of eWOM			
GU ET AL. (2013)	3,000 books and their related eWOM data randomly drawn from a sample of over 3,700,000 unique books collected from Amazon from 07/2005 to 04/ 2006	eWOM data (volume, valence (rating))	Online sales rank		Panel regression
	Main Results	Consumers are more receptive to pWOM on popular products and nWOM on unpopular products; This disparity leads to a rich-get-richer situation, constraining the formation of the long-tail; The increasing availability of eWOM is against the sales of niche products while it supports the sales of popular products; NWOM is damaging niche products more than popular products			
	Limitations	Only the informational value of eWOM is taken into account; In reality, eWOM also exhibits an awareness effect which is neglected			
HO-DAC et al. (2013)	Panel dataset collected from Amazon for Bluray players (n = 78) from 01/2008 to 07/2009 resulting in 3,341 eWOM messages and DVD players (n = 51) from 11/2008 to 06/2009 resulting in 1,664 eWOM messages	eWOM data (volume, valence (rating) and volume of pWOM and nWOM)	Online sales rank	Brand equity of the company; Maturity of product category	Panel regression
	Main Results	PWOM (nWOM) messages show an significant positive (negative) effect on online sales rank for brand with weaker brand equity; Positive and negative eWOM messages are not able to influence sales ranks for brand with strong brand equity; Greater sales lead to more pWOM compared to the increase in nWOM; Weak brands do not seem to be held back by cumulative nWOM so much as they are helped by cumulative pWOM; Contrast to negativity effect			
	Limitations	No consideration of the variance in eWOM judgments; no consideration of expert reviews also available about the products			

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
LI and HIRT (2008)	Theoretical model and subsequent empirical investigation of self selection bias within eWOM reviews over time; 135,485 single review observations for 2,203 books on Amazon.com were extracted between 01/2000 and 07/ 2004	Time since release of eWOM	eWOM valence (rating); Sales rank	Productivity of authors	Theoretical model; Panel regression
	Main Results	eWOM valence: negative self selection, positive self-selection, and no self selection could be shown for different parts of the sample; For the books with productive authors the reviews are more likely to decline over time; Consumer adjustment: people do not fully correct for the inherent review bias; People are not fully aware of the phenomenon; Sales of book: positively associated with the long-term average and temporal component of reviews			
	Limitations	eWOM as expression of overall utility was disregarded; Endogeneity of eWOM volume and valence was not completely taken into account			
LIU (2006)	Consumer movie reviews from Yahoo! Movies; 40 movies released between May 2002 and September 2002 with a total of 12,136 reviews	eWOM data (volume, valence (hand coded))	Offline box office revenue		Panel regression
	Main Results	eWOM: most active in the pre-release period and opening week which means not depend on actual experience; eWOM volume: offers significant explanatory power for box office revenue (informative effect on awareness); eWOM valence: no significant influence			
	Limitations	Focus on only one product category (movies); Consideration of only one web site (Yahoo! Movies), may not be representative			
MOE and TRUSOV (2011)	Consumer product ratings from a national retailer of bath, fragrance, and beauty products after a rating function was introduced on retailer's website in May 2007; 500 products rated and sold between December 2006 and December 2007 (total of 3,801 ratings)	eWOM data (volume, valence (ratings), Variance)	Online sales data	Social dynamics in rating environment	Hazards Models; Simulations
	Main Results	eWOM valence: directly improves sales but the effect is relatively short lives, significantly influenced by previously posted ratings; eWOM variance: generates subsequent eWOM, which facilitates product's recovery in average ratings and product sales; Social dynamics: have a direct effect on sales through a significant effect on ratings valence; Influence future ratings volume and variance but this only indicates an indirect effect on sales			
	Limitations	Data of only one retailer			
PATHAK et al. (2010)	Book recommendation through collaborative filtering on Amazon.com and Barnesandnoble.com; Panel data set of 156 books randomly chosen from any of the top 5,000 sellers on Amazon; Data was collected in 2006	Collaborative recommendations (Strength); eWOM data (volume, valence (ratings))	Online sales rank; Price	Recency, Obscurity	Panel regression
	Main Results	eWOM volume: positive effect on online sales rank; eWOM valence: positive effect on online sales rank; Strength of recommendation: positive effect on sales and on the price of the recommended product; Recency of recommended item: positive effect on sales; Obscurity of recommended item: if the recommended books are not obvious, online recommendations are more influential; Sponsored pair recommendation: has slightly higher effect than regular recommendations			
	Limitations	Focus on only one product category (books); Slightly outdated parameter estimates			

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
REUBER and FISCHER (2011)	Literature review to assess the entrepreneurial potential to successfully pursue international opportunities in internet-enabled markets; 33 Journals traced from 2000 – 2010		No empirical data		Literature Analysis
	Main Results	Propositions for firms competing in internet-enabled markets: The online visibility of a firm is positively related to the firm's successful pursuit of international opportunities; Trustworthiness of a firm positively mediates the relationship between the valence, volume and the firm's successful pursuit of international opportunities; A firm's website customization capabilities are positively related to the firm's successful pursuit of international opportunities; The level of engagement of a firm's online brand community is positively related to the firm's successful pursuit of international opportunities			
	Limitations	Major focus on entrepreneurship literature			
SHIN et al. (2011)	Whole internet (web crawler); Chatter about MP3 players between 06/2007 and 08/2007 on 61 days	eWOM data (volume, valence (algor.))	Market prices	Competition intensity; Price tiers; Brand type	Panel regression
	Main Results	nWOM: past nWOM leads to future decrease in market prices; nWOM effect on current price fluctuation is bigger than the one of past pWOM; Low price products: both positive buzz and negative buzz lead to a price increase; The effect of pWOM is larger for lower-priced items; High price products: the effect of nWOM on price changes is larger for the higher-priced items; Competition intensity: the degree of price fluctuation decreases as the number of e-vendors carrying a product increases; Brand type: the effect of negative buzz on price changes is larger for leading brands; larger effect of pWOM for following brands			
	Limitations	Consideration of prices only from amazon.com; Neglect of individual retailers' pricing strategy; Focus on only one product category (MP3-players)			
SONNIER et al. (2011)	Whole internet (web crawler); Chatter about one technical firm, its products and services from 04/2007 to 12/2007 with about 3,000 post per day; Dynamic model of eWOM	eWOM data (volume, valence (algor.))	Total sales		Panel regression (dynamic)
	Main Results	eWOM valence: negative comments have a negative effect; Positive, negative, and neutral eWOM shows significant impact on sales; Effect sizes for pWOM and nWOM are larger than that of neutral comments; eWOM volume: only measuring volume masks the real effects of eWOM on future sales			
	Limitations	Measurement errors in classifying the valence of a mention; measurement errors in assigning the mention to a firm/product as keywords are not unique; No consideration of the firms' advertising and promotional activities			
STEPHEN and GALAK (2012)	Dataset from Kiva (online marketplace for microloans) about daily loan sales collected between 01/2007 and 03/2008; blog data assessed by Google Blog Search (n = 2,485 posts); community posts of Kivafriends and two discussion forums resulting in overall 23,862 posts	eWOM data (volume blog, volume community, number of community members)	Total sales		Panel regression
	Main Results	Both traditional media and eWOM affect sales; The per-event sales impact of traditional media activity is larger than for eWOM; Because of the greater frequency of eWOM, eWOM's sales elasticity is significantly greater than traditional media's; EWOM appears to play an important role driving traditional media's activity			
	Limitations	Set of media variables could be enhanced; Study deals with an environment without paid media activity as the analyze a NPO			

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
SUN (2012)	Empirical validation of the theoretical model by means of book sales and review data taken from Amazon and Amazon and Barnes & Noble. 667 book analyzed collected from 01/2009 to 05/2009	eWOM data (volume, valence (rating), and variance)	Online sales rank		Game theory and Regression
	Main Results	A higher variance of eWOM valence ratings for a book leads to higher sales if and only if the average rating is low. A higher average eWOM rating score on increases the book's relative sales when the variance is low. The authors propose to include an interaction of valence and variance into empirical models			
	Limitations	No panel regression used; Results should be replicated with a large scale panel dataset			
TUMASIAN et al. (2011)	Political microblogging messages on Twitter; Over 100,000 tweets were analyzed between 08/2009 and 09/2009 in the context of the German 2009 federal election; 70,000 tweets mentioning parties and roughly 35,000 politicians	eWOM data (volume, valence (algor.))	Election results (as political sales)	Sentiment profiles	Sentiment analysis of posts; No multivariate methods used
	Main Results	Political microblogging eWOM: is a platform for political deliberation and is not just used to spread opinions but also to discuss these, dominated by a small number of users; Shows a party bias in user accounts with respect to the volume and sentiment of their political communication; Political microblogging valence: multidimensional sentiment profiles of politicians and parties reflect many nuances of the election campaign; Political microblogging volume: the mere number of messages reflects the election result, with a MAE of 1.65%, even close to traditional polls			
	Limitations	Sample may not be representative of German electorate; Loss of nuances in meaning due to the translation from German to English; Treatment of all messages posted in a certain time as one document: no distinction in positive and negative comment; Study limited to the federal election in Germany			
ZHANG et al. (2010)	Experimental study (n = 150 students) using a fictive Amazon website; Empirical replication study of results from experimental stage with a total of 2,017 product reviews from Amazon; Antivirus software and photo editing software as representatives of different consumption goals	eWOM data (volume, valence (star ratings), Length, Helpfulness); Sales rank	Perceived persuasiveness/helpfulness of review	Consumption goal (regulatory focus)	Experiment; Logit Regression
	Main Results	Experiment: Promotion consumption goal (pWOM more persuasive/helpful than nWOM); Prevention consumption goal (nWOM as being more persuasive/helpful than pWOM); Consumption goal (moderates the effect of review valence on persuasiveness); Empirical replication confirms these results			
	Limitations	Focus on one product category (software programs); Only consideration of Amazon.com as online retailer			
ZHU and ZHANG (2010)	Consumer reviews from the video game market collected on Gamespot.com; All games for PS2 and Xbox from 03/2003 to 10/2005 with a total of 141 game titles	eWOM data (volume, valence (rating), Variance)	Sales data for online and offline sales on the US market	Popularity; Game type	Regression
	Main Results	eWOM volume: has a positive influence on sales of popular and less popular online games, no effect on offline games; eWOM valence: has a positive effect on less popular online games; eWOM Variance: has a negative effect on less popular online games			
	Limitations	Focus on only one product category (video games); Consideration of only one web site (Gamespot.com), may not be representative			

Appendix 3: Overview of Studies - eWOM and Financial Performance

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
ANTWEILER and FRANK (2004)	Stock message boards (Yahoo! Finance and Raging Bull); 45 companies listed in Dow Jones Industrial Average and Dow Jones Internet Commerce Index; Over 1.5 million posts in the year 2000	eWOM data (volume, Average length, valence (IT-coded), pWOM ratio, Disagreement)	Stock/market volatility; Stock return; Trading volume		Panel regression
	Main Results	eWOM volume: positive effect on next day's market and share volatility and trading volume; Small negative effect on returns on the next day for one stock message board; Greater impact on internet firms as well as for smaller-sized trades; Disagreement: increased trading volume; Greater effect for smaller-sized trades			
	Limitations	Difficulties concerning the treatment of periods with no messages posted; Abstract argues that volume induces trading and conclusion tells the opposite			
BIRD and THAPA (2011)	Stock message board (HotCopper.com); 1,000 largest listed companies; 1,5 million posts from 2004 – 2008; Company news data categorized by valence	eWOM data (volume, valence (ratings))	Cumulative excess return; Trading volume; Liquidity measures; Stock volatility	Positive and negative events considered	Event study; Panel regression
	Main Results	eWOM volume: negative (positive) association with excess return for negative (positive) events; Positively associated with stock volatility; eWOM volume and valence: are elevated prior to unscheduled news announcement			
	Limitations	Consideration of only one message board, may not be representative for all stock message board discussions			
CHEN et al. (2012)	Dataset collected for 21 studios in the US-movie industry. Third-party reviews as form of eWOM by professionals like journalists or experts collected from 02/2005 to 04/2006 on the platform Metacritic (member of CNET). Financial data from CRSP database	eWOM data (volume and valence (absolute and relative collected as rating))	Stock return (abnormal return); Stock volatility (risk)		Event study
	Main Results	Professional eWOM exert significant impact on stock returns in the direction of their valence - however, the impact comes from the valence of a review that is measured relative to other, previously published reviews and not from the absolute valence of the review itself; Effect strongest pre-release with a maximum at the day of a movie's release; after sales data gets available, eWOM effect disappears			
	Limitations	Only uses movie industry; Might be possible to replicate with search good data			
COOK and LU (2009)	Stock message board (Yahoo! Finance); 26 companies, 46,691 posts with reported valence	eWOM data (valence (ratings)/ pWOM ratio)	Stock return	Author's credibility	Panel regression
	Main Results	pWOM-ratio: positive predictive power on abnormal stock returns t+1 and t+2; predictive power increases with higher credibility of author			
	Limitations	Consideration of only one message board, may not be representative for all stock message board discussions			
DAS and CHEN (2007)	Stock message boards (small investors); 24 tech-sector stocks of the Morgan Stanley High-Tech Index; 145,110 posts from July and August 2001	eWOM data (volume, valence (IT-coded), Disagreement)	Stock price; Stock volatility; Trading volume		Panel regression
	Main Results	eWOM volume: positive effect on stock volatility; Negative effect on stock price; eWOM valence: positive effect on stock price			
	Limitations	Only stocks from tech-sector are looked at			

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
Hu et al. (2011)	Firms blog visibility (blog crawler); 315 S&P 500 firms	Blog visibility	Book-market ratio; Trading volume		Panel regression
	Main Results	Blog visibility: positively associated with the value of a firm; Past blog visibility: Granger causes future trading volumes			
	Limitations	eWOM valence not considered and focus only on US firms			
Hu et al. (2012)	Dataset consists of 404 S&P 500 firms analyzed between 03/2006 and 08/2006. Blog visibility was collected from www.BlogPulse.com via a tracking tool. Media coverage was collected from Factiva and financial data from CompuStat and the CRSP database	Blog visibility	Stock return (abnormal return)		Portfolio study
	Main Results	Stocks with low blog visibility earn higher returns than stocks with high blog visibility; This effect is more prominent for stocks with low institutional ownership; The blog effect suggests that it can be attributed to the limited attention theory and cannot be arbitrated due to investors' self-attribution and short-sale constraints			
	Limitations	Blog visibility not controlled for valence which might be problematic if blog messages are of negative tonality			
LUO and ZHANG (2013)	Dataset similar to LUO et al. (2013b). EWOM buzz measured by CNET (17,486 consumer reviews for 1,939 unique products of 9 firms from IT hard- and software collected from 08/2007 to 07/2009)	eWOM data (volume and valence (ratings))	Stock return (abnormal return); Stock volatility (i.e., risk)		Panel regression (VAR)
	Main Results	EWOM (both volume and valence) exhibits a substantial role in explaining firm value; A competing firms' eWOM volume and valence are also associated with firm value; eWOM drives traffic and vice versa which leads to a stronger effect when both are considered jointly			
	Limitations	No causality assumptions can be made; Same dataset used as LUO et al. (2013b)			
LUO et al. (2013b)	Dataset from computer hardware and software industries for 9 cross sections. Daily data collected from Alexa, CNET (eWOM IT crawled: 17,486 consumer reviews for 1,939 unique products of the targeted firms), Lexis/Nexus, Google search, CRSP, COMPUSTAT, and Yahoo Finance from 08/2007 to 07/2009 resulting in 4,518 observations	eWOM data (volume, valence (ratings))	Stock return (abnormal return); Stock volatility (i.e., risk)		Panel regression (VAR)
	Main Results	eWOM data (i.e., web blogs and consumer ratings) are leading indicators for firm equity value; eWOM is superior to other social media metrics like Google searches or web traffic; Especially consumer ratings as measure of eWOM valence shows highest predictive power for firm value and risk; eWOM also has shorter wear-in time and negative eWOM on blogs has the shortest wear-in time in predicting firm equity value			
	Limitations	The research design cannot assure the causality of the predictive value of eWOM and social media which calls for field experiments			
MCALISTER et al. (2011)	Whole internet (web crawler); eWOM of the firm/product/services; One technical products firm observed in 2007	eWOM data (volume, valence (IT-coded), Disagreement, Authors/Sites)	Stock return		Panel regression
	Main Results	Volume of total and neutral eWOM: both have a positive effect on stock returns			
	Limitations	Results may be invalid for non-technical firms; No consideration of the firm's use of its marketing mix during the observed period of time			

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
OH and LIU SHENG (2011)	Microblogging stock messages (Stocktwits.com and Yahoo! Finance); 72,221 posts for 1,909 stock tickers from 05/2010 to 08/2010	eWOM data (valence (IT-coded))	Simple stock return; Market-adjusted stock return		Theoretical model development and validation
	Main Results	Valence: helps to predict future stock price movements (valuable stock investing information included); nWOM has higher predictive accuracy than pWOM			
	Limitations	Economic sway, cyclical stocks, or other seasonal and political influences may have biased the results as the data collection period is relatively short			
THAPA and BIRD (2010)	Stock message board (www.hotcopper.au); 440 companies listed on Australian Stock Exchange; 981,200 posts from 2004 – 2008	eWOM data (volume)	Stock return		Panel regression
	Main Results	eWOM volume: positively related to stock return for distressed or high momentum stocks; No evidence on average of stocks returns			
	Limitations	Only Australian companies are investigated; Consideration of only one message board, may not be representative for all stock message board discussions			
TIRUNILLAI and TELLIS (2012)	Product reviews UGC (web crawler) on Amazon, Epinions, and Yahoo Shopping; 15 companies from six markets listed on NASDAQ, NYSE, or AMEX with 347,628 reviews from 06/2005 to 01/2010	eWOM data (volume, valence (ratings and IT-coded))	Stock return; Idiosyncratic risk; Trading volume		Panel regression
	Main Results	Volume: predicts returns and trading volume; Pure volume has the strongest relationship with returns in the short and long term; Numerical Ratings: no significant effect on returns; nWOM and pWOM: nWOM has stronger influence on returns than pWOM (pWOM not significant); pWOM has positive influence on idiosyncratic risk			
	Limitations	Consideration of only two forms of UGC (product reviews and product ratings); Assessment of the impact of UGC on stock market performance on a daily level: problems with non-synchronous trading			
TUMARKIN and WHITE LAW (2001)	Stock message boards (RagingBull.com); 73 internet sector companies; 181,633 posts from 04/1999 to 02/2000	eWOM data (volume, valence (IT-coded))	Stock return; Trading volume		Event Study; Panel regression
	Main Results	Volume: no effect on stock returns (consistent with market efficiency); Positive effect on trading volume (t and t+1 day); Volume and valence: stock returns from internet service sector are not predictable by message board data; <i>Stock returns: higher posting volume after high stock returns</i>			
	Limitations	Consideration of only one message board which is a public bulletin board, results may be different for private bulletin boards			
WYSOCKI (1999)	Stock message board (Yahoo! Finance); 50 stocks with highest eWOM volume for time series analysis from 01/1998 to 08/1998; 1,941 stocks in cross-sectional sample from 12/1997 to 07/1998	RoE; Stock return; Trading volume; Market value equity; Traded on NYSE	eWOM volume		Logit-Regression; Panel regression
	Main Results	Posting volume in t: No predictive ability for stock returns in t+1; 100% increase overnight leads to a 0.18% average abnormal return			
	Limitations	Consideration of only one message board, may not be representative for all stock message board discussions; Main focus of paper is reversed causality of what drives eWOM volume			

Appendix 4: Overview of Studies - The Company and its Dual Role

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
BAMPO et al. (2008)	Theoretical model about the spread of viral marketing messages in social network structures; Data from General Motors in Australia	Initial seeding of promotional messages for viral campaign; Probability of forwarding	Viral marketing campaign success	Social network structures	Theoretical model; Empirical validation; Simulation study
	Main Results	Scale-free networks are very efficient for viral campaigns; clustered networks not particularly efficient, as they temper viral effects; When using a high initial number of seeds, the structure of the digital network is less important; When using lower levels of initial seeding, the network structure has a marked impact; Message characteristics and creative execution affect how often the content is forwarded, and, hence, the number of transmissions			
	Limitations	Model does not take the notion of receptivity into account i.e., influential users who are highly effective in persuading others to adopt an idea			
BERGER and MILKMAN (2012)	Three studies: I. Investigates linkage between content characteristics and virality (6,956 articles on the New York Times website between 08/2012 and 11/2012) II. Experiment: analyzes causal impact of specific emotions on sharing (n = 49) III. Experiment: tests how deactivating emotions affect transmission (n = 47)	Prompted emotions of content	Virality of news articles	Arousal level as emotional intensity measure	Logistic Regression; Two Experiments
	Main Results	Positive content is more viral than negative content and positive and negative emotions characterized by activation or arousal (i.e., awe, anxiety, and anger) are positively linked to virality; Emotions characterized by deactivation (i.e., sadness) are negatively linked to virality; A customer service experience will more likely be shared with others when it evoked more anger; When a story evoked more sadness, it decreased arousal, which in turn decreased transmission			
	Limitations	Only self reported probabilities of viral transmission were assessed; Virality only measured with e-mail forward option			
CHEN and XIE (2008)	Preliminary empirical study to test differences between third party reviews (CNET.com) and eWOM (Amazon.com) about 90 digital camera models from June 2004 to September 2005; Subsequent theoretical two-period model with a monopoly seller carrying multi-attribute products	No further empirical investigation			Regression; Game theoretical model
	Main Results	Third party review ratings do not offer the same information as eWOM ($r = 0.267$); Product attribute information provided by the seller and eWOM will interact with each other; The seller's optimal response to eWOM: Increase the product attribute information in response to consumer reviews for low-cost products, but decrease them for high-cost products; Offering the possibility to post eWOM can benefit products with a sufficient number of novice consumers; Offering the possibility to post eWOM can hurt the seller if the segment of expert consumers is relatively large			
	Limitations	No empirical validation of proposed model			

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
CHEN et al. (2011a)	Dataset of eWOM about automobile models of the year 2001 from three review websites and of the year 2008 from four leading review websites; Analysis of how eWOM volume and valence are connected to price and quality of the offered products throughout internet usage stages	Price; Quality	eWOM (volume, valence (rating))	Internet usage stage	Regression
	Main Results	eWOM volume: decreases with product price in the early stage of internet usage (2001); U-shaped relationship with price in later stages (2008) such that more volume for extremely low-or high-priced products eWOM valence: U-shaped relationship with price especially within the 2001 dataset – higher overall ratings for low- or high-priced products; Positive relationship with product quality across all years			
	Limitations	Only automotive industry was looked at; Main focus of paper is reversed causality of what drives eWOM			
CLEMONS (2009b)	Theoretical contribution about monetizing the value of social networks, the loss of power of traditional advertising, and the new role of social media in the marketing landscape	No empirical data			Theoretical contribution
	Main Results	In categories where consumers seek to avoid bad experiences, the absence of negative ratings (not the presence of positives) correlates with sales; 5 value propositions of social media: ethnographic observation, usage fees; revenues from selling, replace traditional advertising; create synergies; All social networking websites that attract a following offer at least two of the following 4Ps: Personal, Participatory; Physical; Plausible; Sponsored content more promising than ads; Greater impact of eWOM reviews if posted on a professional rating site or a community content site than on the manufacturer's site			
	Limitations	No empirical data			
CLEMONS et al. (2006)	Empirical analysis about how eWOM can be used to evaluate the effectiveness of product differentiation strategies; 281,868 reviews about 1,159 US craft brewers in the USA extracted from ratebeer.com between 04/2000 and 07/2004	eWOM data (valence (rating), Variance)	Product differentiation strategies (sales growth)		Regression
	Main Results	eWOM variance: dispersion of ratings is positively associated with sales growth; eWOM valence: average of the high-end reviews is positively correlated with sales growth; average of low-end reviews is not negatively correlated with sales growth; It is more important to have some customers who love you than a huge number of customers who merely like you; Firms that seek to provide products that are targeted at consumers who will have extreme reactions will grow faster			
	Limitations	Sales data-base contains only company-wide sales figures and no controls for advertising spending			
DE BRUYN and LILJEN (2008)	Experimental study simulating a viral marketing campaign by inviting to an online survey; 634 students participated as initiators of email chains	Viral eWOM message; Tie strength; Demographics; Perceptual affinity	Awareness; Interest; Product adoption		Experiment
	Main Results	Networks of friends are more suited to the rapid and effective diffusion of peer-to-peer online referrals than networks of professionals/colleagues; Close relationships can be effective in capturing recipients' attention and creating awareness (e.g., to drive traffic to a website), they had no influence at later stages			
	Limitations	Generalization to more traditional WOM communications about products or services questioned			

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
DEIGHTON and KORNFIELD (2009)	Theoretical contribution about the changing marketing landscape especially consumer empowerment		No empirical data		Theoretical contribution
	Main Results	Four interactive marketing paradigms proposed: tracing (activity and thought); Exchange (property, social, cultural); A new marketing landscape arises: competition for search terms; Access and identity; Service, reputation and reliability, Communities; Buzz markets; Social media channels can be classified on two dimensions: Brand intention → information vs. impartation of meaning; Attribute of consumer constructed in the interaction → identity vs. accessibility			
	Limitations	No empirical data			
DELLAROCAS (2006)	Game theoretic model development about the strategic manipulation of eWOM data by companies		No empirical data		Game theoretic model
	Main Results	If every firm's manipulation strategy is an increasing (decreasing) function of firm's true quality, strategic manipulation of online forums increases (decreases) the information value of a forum to consumers → Scenario where only the consumer benefits is possible; Equilibria where strategies are monotonically increasing (decreasing) functions of a firm's true quality exist in settings where the firm's net payoff function, inclusive of the cost of manipulation, is supermodular (submodular) in the firm's quality and manipulation action; In a broad class of settings, if the precision of honest consumer opinions that firms manipulate is sufficiently high, firms of all types, as well as society, would be strictly better off if manipulation of online forums was not possible; Current situation: "Rat race" - all firms have to manipulate posts, because if they don't, consumer perceptions will be biased against them			
	Limitations	No empirical validation			
DROGE et al. (2010)	Exploratory study about the role of blog communities in new product development; Eleven tech-blogs analyzed between 01/2006 and 02/2006 (70 postings; 60 for major (i.e., Engadget and Gizmodo) and 10 for smaller blogs)		Only exploratory and descriptive analysis of extracted data		Descriptives; Content analysis
	Main Results	The major content for new product development managers can be found in the original blog posts and about three days of readers comments; Crucial topics: how/when the product will be used, product information, trend ratings; Blogs seem suitable for market research purposes, but in the later stages (e.g., during early commercialization); Content analysis revealed that of all postings 95.71% containing product information, 87% mentioning features, 52.86% giving overall evaluations, 28.57% posting about performance, 27.14% mentioning compatibility, ease of use (20%), and style (17.14%)			
	Limitations	Small sample size only in the technology sector – only exploratory approach			
GALEOTTI and GOYAL (2009)	Game theoretical model with main constructs: Social network dispersion; Advertising spending; Value of knowing the network; Firm outcomes; Adoption externalities		No empirical data		Game theoretic model
	Main Results	eWOM: differs across products; increases sales and profit; Value of information about the SN is higher for more dispersed product categories (adoption externalities); Greater social connectivity per se does not provide an argument for greater investments in network information; Strategies: when a firm conditions strategy on out-degrees it is optimal to target poorly connected individuals; When a firm conditions strategy on in-degrees it is optimal to target the most connected ones; Advertising: eWOM communication is a substitute for firm advertising			
	Limitations	Restricted to networks with no clustering; Focus on the case of a monopoly firm			

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
GODES and MAYZLIN (2009)	Field study for two eWOM creator subpopulations: customers of a restaurant chain (Rock Bottom Brewery; n = 381) or independent eWOM creators from a marketing agency (BzzAgent n = 692) between 04/2003 and 06/2003; Experimental study with n = 96 students confirming the results	CGC – eWOM (Source (customer vs. non-customer))	Offline Firm Sales Number of eWOM episodes reported	Loyalty towards brand of sender; Opinion leadership; Product awareness	Panel regression; Experiment
	Main Results	The sales impact of incremental WOM from a less loyal customer is higher than that from a loyal customer; The sales impact of incremental WOM to an acquaintance is higher than that to either a friend or a relative; Less-loyal customers should be recruited to participate in a company induced WOM campaign. Their recommendations are more likely to be received by people who are currently less experienced with, or less informed about, the firm's products; While opinion leadership is associated with the creation of more WOM for loyal customers, this is less true for less-loyal customers. For products with low or moderate initial levels of awareness, loyal customers are not necessarily the cornerstone of a successful WOM campaign			
	Limitations	Difficulties to control for all the differences between the customer and the non-customer populations			
HENNIG-THURAU et al. (2010)	Framework of new media's impact on relationships with customers (theoretical contribution); Key new media phenomena are identified which companies should take into account when managing their relationships with customers	No empirical data			Theoretical contribution; Literature review
	Main Results	Definition of social/new media: Websites/channels are digital, pro-active, visible, real-time and with memory function, ubiquitous, and networks; Marketing how it has been: customers were predominantly passive "receivers" of marketing and media information; Marketing how it is today: marketers have lost control over their brands, but now participate in a "conversation" about the brand; Social Media requires a shift in marketing thinking → consumers as highly active partners (interconnected customers, producers, and retailers); New Media and current research splits up in two major areas: information & services and technologies; Information and services: New multimedia services, eWOM, consumers as retailers, and online social communities			
	Limitations	No information how studies were identified; Only vague guidance for practitioners			
HINZ et al. (2011)	Comparison of four different seeding strategies for viral marketing campaigns; Experimental study in a controlled laboratory setting (n = 120 students); Experimental field study (n = 1,380 social network of all students enrolled) and a empirical dataset from text message based viral campaign of mobile phone provider (n = 208,829)	Seeding strategies (High degree - hubs; Low degree - fringe; High betweenness - bridges; Random - control)	Campaign reach (participants, referrals, successful referrals)		Experiment; Logit regression
	Main Results	Highest number of referrals, across various settings, if message seeded to hubs (high-degree seeding) or bridges (high-betweenness); Comparable results of both strategies; Both outperform the random strategy (+52%) and are up to eight times more successful than seeding to fringes; The superiority of the high-degree seeding strategy rests on the increased activity level of hubs and not their higher persuasiveness			

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
	Limitations	Student sample and the artificial information content of the experiments; Real life application only compared high- and low-degree and random seeding strategies and assumed a constant social network			
Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
HO and DEMPSEY (2010)	Empirical study about factors influencing forwarding behavior in a viral marketing campaign; Framework: FIRO theory; Survey with undergraduate students (n = 582)	Inclusion (Need to belong, Individuation); Altruism; Control: Consumption of online content	Forwarding online content		PLS
	Main Results	Motivations for forwarding online content within a viral marketing campaign: inclusion (individuation), altruism, control, and amount of internet content; A viral marketing campaign has a greater chance of success if the marketer is able to develop marketing communication strategies that resonate with the target group; Appeals to the key motivations for sharing information			
	Limitations	Sample of college students belong to the group of heavy internet users which might bias results			
KOZINETS (2002)	Theoretical contribution introducing Netnography for market research purposes in online communities; Short empirical demonstration/validation within the online community alt.coffee Usenet newsgroup (n = 117 postings)	Just small demonstration sample of the mainly theoretical contribution			Netnography
	Main Results	Netnography is faster, simpler, and less expensive than traditional ethnography and more naturalistic and unobtrusive than focus groups/interviews; Generalizations to markets or communities other than the one studied, online or offline, must have corroborating evidence; Understanding the language of consumer segments and its underlying social motivations is a key aspect in achieving market orientation			
	Limitations	Example only vaguely shows insights into the complete procedure			
KOZINETS et al. (2010)	Qualitative analysis of a seeding campaign for a new camera equipped cell phone (n = 83 blogs; extraction of n = 6,722 posts; 220 of bloggers about the phone and 700 comments from readers); Six major US cities and on blogs	Qualitative analysis of blog posts to investigate firms' intention of influencing consumer-to-consumer communication			Qualitative content analysis
	Main Results	Each blog contains a particular history and perspective in its character narrative: attracts a certain audience and sets the audience's expectations; A particular WOM marketing promotion must be presented in a manner that is congruent with the ongoing character narrative, communications forum, and communal norms prevalent in that WOM environment; Network of communications offers four social media communication strategies: evaluation, embracing, endorsement, and explanation; Communal WOM does not simply increase/amplify marketing messages; Messages and meanings are altered in the process of embedding them; Assessing a WOM marketing campaign only by volume of positive mentions is far too short			
	Limitations	No validation of proposed network narratives model			
KRISHNAM URTHY and KUCUK	Empirical investigation of the connection between brand value and anti-brand site presence; Top 100 brands of business week's 2004 list resulting in 90 companies of 2004 and 2005; Anti-brand websites were identified in 05/2005	Brand value; Anti-brand site presence	Brand value; Anti-brand site presence		Logistic regression

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
	Main Results	Brand value: the higher the brand value of a company the more presence of anti-brand sites; Presence of anti-brand sites: associated with negative changes in brand value; Language on anti-brand sites: three types of speech: market, ideological, transactional ; Market speech has high correlation with brand value			
	Limitations	Only use of aggregated data – individual data would be necessary to fully understand the phenomenon			
Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method
LEVIN and MILGROM (2010)	Investigation of differences between traditional advertising and online advertising and discussion of hyper-heterogeneity, of experience of some “commodity” markets and introducing the idea of conflation	No empirical data			Theoretic contribution
	Main Results	Standardization: reduction of measurement costs and adverse selection and facilitation of the creation of futures contracts and related markets; Advertising is matched finely (i.e., market for online search terms) despite the set of products offered in the market’s being much coarser; Narrow targeting on Facebook currently is cheaper than a broader range of target audience; It is not clear that future display advertising on the internet will involve continued increases in fine targeting			
	Limitations	No empirical validation or game theoretical model			
LIN and HUANG (2006)	From a case study of a 2003 private website promoting tourism to Greece in Taiwan implications are derived for the proper website design to activate eWOM messages and to make content go viral; The AIDA model is used to classify 301 eWOM messages left on the website	No empirical data			Case study approach; Content analysis
	Main Results	Critical success factors of viral marketing campaigns are: current atmosphere within target audience (i.e., fear of SARS), identity of content creator, contribution to individuals realization of their dreams, originality of content and creation of desire, simple website content			
	Limitations	No empirical evidence			
MAYZLIN (2006)	Game theoretic approach to determine the influence of promotional marketing messages (CGC) that are disguised as consumer recommendations	No empirical data; Models looked at a market with one inferior and superior good			Game theory
	Main Results	Consumers read messages online that help them decide on the identity of the superior product – they reduce uncertainty; Advertising and eWOM are substitutes when advertising messages are anonymous; A unique equilibrium is identified where eWOM is persuasive despite the promotional chat activity by competing firm; In this equilibrium, firms spend more resources promoting inferior products, in striking contrast to existing advertising literature			
	Limitations	No empirical validation of proposed model			
ONISHI and MANCHANDA (2012)	Empirical analyses in movie and cellular phone category to assess whether new and traditional media reinforce or damage each other’s effectiveness; 12 movies that were released from 01/2007 to 08/2007; Data from five Japanese cell phone companies from 11/2006 to 04/2008	CGC (Number of blogs, valence of blogs); Advertising spending	Number of customers; Number of blogs		Panel regression

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method	
	Main Results	The volume of blogs about a product and the valence of recent (current) blogs are predictive of market outcomes; The effect of blogs and advertising is synergistic on market outcomes; Pre-launch advertising spurs blogging activity, but become less effective in inducing blogging activity post-launch; Market outcomes do have some effect on blogging activity				
	Limitations	Only aggregated data were analyzed; Only blogs were taken as representatives for social media				
TRUSOV et al. (2009)		Empirical study of the effect of eWOM marketing on member growth at an internet social networking site in comparison to traditional marketing vehicles; Data between 02/2005 and 10/2005 from a major social networking site about sign-ups and eWOM referrals	eWOM marketing, Traditional offline marketing events	Membership growth (customer acquisition measure)		Panel regression
	Main Results	The eWOM marketing effect remains significant from zero for approximately three weeks vs. traditional marketing tools of media and events persists just a few days; eWOM shows a larger short term effect on customer acquisition as well as a substantially longer carryover effect than traditional advertising; A simulation study shows that each outbound referral sent out is worth approximately \$0.75 per year in increased advertising revenue				
	Limitations	Only one social media site was looked at and the product "membership on social networking site" might not be representative for general marketing assumptions				
VAN LAER and DE RUYTER (2010)		Three experimental studies (n = 153/145/95 students) investigating the determinant of effective corporate responses to negative consumer blog posts; Healthcare, public railway, and automotive context	Response format; Response content; Replying person	Intention to switch; Perceived integrity	Independent mental priming (empathy vs. imagery)	Experiments
	Main Results	Analytical response format: greater integrity if the response content is a denial rather than an apology; Consumers switch less often if the response content is a denial rather than an apology; Narrative response format: Greater integrity if the response content is an apology rather than a denial; Consumers switch less often if the response content is an apology rather than a denial; Mental priming: Greater integrity if they reply with empathy rather than imagery; Replying person: greater integrity if the responsible employee, rather than the company's spokesperson, issues the apology				
	Limitations	Missing incorporation of some other moderating variables, such as loyalty toward the company or brand; Assumption that companies do take over responsibility				
VAN DER LANS et al. (2009)		Theoretical model development to predict how many customers a viral marketing campaign will reach and how marketers can influence this through marketing activities; Empirical application of proposed model to an actual viral marketing campaign of a financial service provider (n = 228,351 customers) between 01/2005 and 05/2005	Traditional marketing activities; Banner advertising; Seeding e-mails	Number of participants within viral marketing campaign		Theoretical model development, Panel regression

Study	Data Base/ Industry Branch/ Sample	Exogenous Variable	Endogenous Variable	Moderators	Method	
	Main Results	The viral branching model provides the opportunity to participate in a viral marketing campaign by (1) opening a seeding e-mail from the organization, (2) opening a viral e-mail from a friend, and (3) responding to other marketing activities such as banners and offline advertising; Critical factors for viral campaigns are: number of seeds, number of e-mails sent by participant, and participants' switching probabilities through viral stages; Customers seem to read their e-mails less frequently during weekends compared to weekdays; Marketing activities following a viral campaign show a stronger long-term effect: Combination seems useful				
	Limitations	Only focus on the pure number of participants – no information about the quality of the lead or website behavior on the landing page of campaign				
VAN NOORT and WILLEMSSEN (2012)		Experimental study about effective means for companies to counteract nWOM; Fictitious blog posts dealing with a car recall in the automotive industry; n = 163	CGC; Webcare intervention strategy (proactive vs. reactive)	Brand evaluation	Platform type; Communication style	Experiment
	Main Results	Webcare interventions: levels off negative effects on brand evaluation among consumers; Proactive intervention strategy: engenders more positive brand evaluations in a brand-generated than consumer generated platform, perceived as higher in natural human voice in a brand-generated than consumer-generated platform; Reactive intervention strategy: positive brand evaluations, irrespective of the platform; Perceived as high in natural human voice, irrespective of the platform				
	Limitations	Only one industry/product type was looked at; only scarce information provided about the conducted treatment				
VILLANUEVA et al. (2008)		Theoretical model that captures success measured by each acquired customer's contribution to overall customer equity split by acquisition channel; Empirical test of model with data from web hosting company from 70 weeks and self-reported "How did you hear about the company"	Marketing acquisition; WOM acquisition	Number of new registrations; Number of WOM registrations; Customer equity		Theoretical model development; Panel regression
	Main Results	Marketing induced customers create higher short term value than WOM induced customers; WOM customers add nearly twice as much long-term value to the firm; Firms that can afford to build a customer base organically (i.e., through WOM) face a better long-term profitability outlook and can spend less on customer retention; Financial incentives to boost WOM acquisition are an appropriate tool to stimulate forwarding behavior				
	Limitations	Self reported acquisition channel data was used and WOM was operationalized in very wide sense by also including third party reviews and newspaper articles				
WINER (2009)		Theoretical contribution about how the evolution of new media has changed the media landscape; Challenges for marketers and research are derived using management challenges as a framework	No empirical data			Theoretical contribution
	Main Results	New media is interactive and digital and shows three different types: intrusive (e.g., pop-ups), non-intrusive (e.g., streaming audio/video), and user-generated; Current key-questions of marketing are: Is new media a supplement, which is adding some frequency to reach goals, or a complement, delivering something different? Right content for right medium and loss of brand control; How to measure outcomes and allocate budgets?				
	Limitations	Framework not derived from theory and research issues seem to be derived from a practical perspective rather than a research point of view				

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