City Research Online

City, University of London Institutional Repository

Citation: Gottschalk, S. A. & Mafael, A. (2017). Cutting Through the Online Review Jungle — Investigating Selective eWOM Processing. Journal of Interactive Marketing, 37(1), pp. 89-104. doi: 10.1016/j.intmar.2016.06.001

This is the accepted version of the paper.

This version of the publication may differ from the final published version.

Permanent repository link: https://openaccess.city.ac.uk/id/eprint/20801/

Link to published version: https://doi.org/10.1016/j.intmar.2016.06.001

Copyright: City Research Online aims to make research outputs of City, University of London available to a wider audience. Copyright and Moral Rights remain with the author(s) and/or copyright holders. URLs from City Research Online may be freely distributed and linked to.

Reuse: Copies of full items can be used for personal research or study, educational, or not-for-profit purposes without prior permission or charge. Provided that the authors, title and full bibliographic details are credited, a hyperlink and/or URL is given for the original metadata page and the content is not changed in any way.

City Research Online: http://openaccess.city.ac.uk/ publications@city.ac.uk

Cutting Through the Online Review Jungle – Investigating Selective eWOM Processing

Sabrina A. Gottschalk[1] and Alexander Mafael[1]

Abstract

Consumers frequently rely on online reviews, a prominent form of electronic word-of-mouth (eWOM), before taking a purchase decision. However, consumers are usually confronted with hundreds of reviews for a single product or service, as well as rich information cues on review websites (review texts, helpfulness ratings, author information, etc.). In turn, consumers face more information cues on online review websites than they can or want to process, and are likely to proceed selectively. This paper investigates selective processing of such eWOM information cues. Results of study 1, an exploratory study using verbal protocols, confirm that consumers display selective eWOM processing patterns and are able to articulate them. Study 2 develops and applies a measurement instrument to capture these patterns. A subsequent cluster analysis on members of a large-scale online panel (N=2,295) indicates five prominent eWOM processing types, termed "The Efficients", "The Meticulous", "The Quality-Evaluators", "The Cautious Critics", and "The Swift Pessimists". Insights of this study can help firms to better understand consumers' eWOM processing and improve the user-friendliness of online review websites.

Keywords: Electronic word-of-mouth (eWOM); Online reviews; Information overload; Selective information processing; Measurement instrument; Verbal protocols

[1] Both authors contributed equally to this manuscript.

Freie Universität Berlin, School of Business and Economics, Marketing Department, Arnimallee 11, 14195 Berlin, Germany
E-mail addresses: sabrina.gottschalk@fu-berlin.de (S.A. Gottschalk), alexander.mafael@fu-berlin.de (A. Mafael).

1. Introduction

1.1 Motivation

Electronic word-of-mouth (eWOM) has a strong impact on consumers (King, Racherla and Bush 2014). Online reviews, as a prominent form of eWOM, are an integral part of the online environment and consumers frequently employ them during their information search (e.g., Duan, Gu and Whinston 2008; Liu 2006). As many as 78% of online Americans aged 18-64 agree that online reviews help them decide whether to purchase a product (Ipsos 2012). However, when consumers want to consult online reviews, they usually find a very large and diverse set of hundreds or even thousands of reviews for a single product or service. For example, over 14,000 online reviews are currently available for the “Kindle Paperwhite” on *amazon.com*, and the hotel “Hilton Garden Inn Times Square in New York” has over 4,000 reviews on *tripadvisor.com*. Even convenience goods like a “Paul Mitchell hair shampoo and conditioner set” has more than 280 reviews on *amazon.com.* Online reviews encompass rich information about experiences with a product or service. In addition, review websites like *tripadvisor.com* or *amazon.com* complement online review texts with other eWOM information cues, such as summary statistics, helpfulness ratings, or author information.

This large number of eWOM information cues poses a challenge for the information seeker and a potential threat of information overload (Jacoby 1977; Jacoby, Speller, and Berning 1974). In order to reduce cognitive load when processing this body of eWOM information cues, consumers can be expected to proceed in a manner that is characterized by selective attention to the different information cues available (Kuan et al 2015). This paper aims to examine *selective eWOM processing patterns*. We define a selective eWOM processing pattern as the combination of eWOM information cues which a consumer processes as part of his or her decision-making, while deliberately disregarding other available eWOM information cues. More specifically, we address two main research questions:

(1) How can selective eWOM processing patterns be measured?

(2) Which prominent types of eWOM processing can be identified among consumers?

We address these research questions in two studies. After a literature review, we gain exploratory insights and locate relevant eWOM information cues through qualitative research. Next, we construct a measurement instrument for these information cues, which allows us to identify different prominent patterns of selective eWOM information processing through clustering mechanisms. We relate cluster membership to relevant respondent characteristics through profiling analysis. This leads to a typology of how different groups of consumers process eWOM information cues for decision making. At the end, we come to a general discussion and limitations section. Please see figure 1 for an overview of the research process.

[Figure 1 goes about here]

1.2 Contribution

This paper makes two main contributions. First, we add to the literature stream on electronic word-of-mouth. EWOM-communication is defined as "word-of-mouth communication on the Internet, which can be diffused by many Internet applications such as online forums, electronic bulletin board systems, blogs, review sites, and social networking sites" (Goldsmith and Horowitz 2006). Prior studies have mostly assessed the impact of eWOM on consumers either on an aggregated level (e.g., Chevalier and Mayzlin 2006), where processing of specific eWOM information cues is indiscernible, or in controlled laboratory experiments, where consumers are often confronted with a small set of only five or ten online reviews (e.g., Kronrod and Danziger 2013, Park and Lee 2008). In turn, research on online reviews has largely neglected the role of information overload and subsequent responses of consumers in this context. By introducing the concept of consumers' selective processing of a large number of eWOM information cues, we offer a more fine-grained and realistic picture. As part of this examination, we systematically explore, formalize and validate a measurement instrument of selective eWOM processing. Our research also has important managerial implications. Online reviews have become a success factor of many business models (French, LaBerge and Magill 2011). Our measurement instrument can assist managers in uncovering selective eWOM processing patterns among different sample populations and the survey-based methodological approach is more practicable than time-consuming observational studies. The identification of different processing types can help to improve the user-friendliness of review websites, allows improved directed customization of content, and increases the potential impact of such information. Companies increasingly tailor website experience to individual visitors' informational needs, e.g. by providing recommendations based on prior information search or purchase history (Häubl and Trifts 2000). Adding insights about consumers' unique ways of dealing with the different eWOM information cues could further enhance user experience and contribute to decision proficiency.

Second, we contribute to the theoretical foundations of information overload and information processing. A long-standing literature stream has shown that humans rely on selective information processing strategies when facing information overload (Fischer, Schulz-Hardt and Frey 2008). Prior studies have for example examined how consumers employ heuristics to choose between product alternatives or between product attributes (e.g. Payne, Bettman, and Johnson 1988). In contrast to product attributes, which represent information cues that vary from product to product, online review websites are modern information environments that convey relatively consistent sets of information cues.

We define eWOM information cues as elements of information that constitute the structural properties of online review websites. One could, for example, regard the available number of online reviews for a product as one eWOM information cue and information about the authors of reviews as another cue. Structural properties of online review websites are highly similar across a large variety of different online review websites (see figure 2 for a comparison of the eWOM information cues of two prominent online review websites). Individuals are prone to display repeat patterns of website navigation in order to reduce cognitive effort (Johnson et al. 2004). As eWOM users will repeatedly be confronted with similar information cues, it is highly sensible to examine selective eWOM processing patterns. Our research therefore extends past findings on information load and processing to present-day online settings which are heavily frequented by modern consumers. This constitutes an important step towards a better understanding of consumer information processing in the context of eWOM information.

[Figure 2 goes about here]

2. The Impact of eWOM Information on Consumers

In comparison to traditional word-of-mouth (WOM), there are several distinguishing aspects of eWOM: (1) consumers have the ability to access and learn from a wide range of opinions from strangers (Libai et al. 2010), (2) these opinions are usually distributed across a wide range of valence (Purnawirawan, de Pelsmacker and Dens 2012), and (3) online reviews are of particular interest for retailers and website providers because on-site technological devices allow for close monitoring and steering of information (Burke 2002). These particularities of eWOM necessitate a more detailed investigation of the specific mechanisms that underlie the impact and processing of eWOM (Floyd et al. 2014). In this study, we focus on online reviews as one prominent form of eWOM due to the increasing relevance and popularity of online review websites (e.g., *epinion.com*, *tripadvisor.com*) and because online reviews constitute the primary source of non-marketer information supplied by many retailing sites (e.g., amazon.com, booking.com). Among the various information sources that are relevant to consumers, online review websites are continuously growing in both impact and size (Deloitte 2014). Increasingly, retailers undertake efforts to actively incorporate online reviews in their websites by inviting consumers to write and share product evaluations (Khan 2015).

A large body of literature employs models that focus on the impact of online reviews on an aggregate level (see King, Racherla, and Bush 2014 for a recent review). In general, these studies show a considerable impact of various online review information cues on cumulative economic outcomes. More specifically, an array of studies report an effect of valence (Chevalier and Mayzlin 2006), of volume (Liu 2006), or of both factors simultaneously (Duan, Gu and Whinston 2008) on sales and integrate eWOM information into forecasting models (Dellarocas, Zhang and Awad 2007). While these studies all confirm the strong aggregate influence of online reviews, we expect that individuals do not process all available eWOM information cues in a uniform manner but differ in their focus on eWOM information cues, resulting in a selective procedure. For instance, current research stresses that it remains largely unclear which characteristics of a review determine whether it is useful for the reader (Mudambi and Schuff 2010). With the use of text mining and sentiment analysis, Mudambi and Schuff (2010) show that both, peripheral cues (review rating, reviewer credibility) and central cues (content) can influence helpfulness. Hence, consumers may differ in their focus on information cues. In a similar vein, research on the usefulness of positive and negative reviews for decision making is inconclusive. Floyd et al. (2014) investigate the effect of eWOM on sales elasticity and find that especially review valence has a strong impact on product sales elasticities. In another study, Yin, Zhang, and Bond (2014) find that consumers consider negative reviews more useful. In contrast, Pan and Zhang (2011) find evidence that positive reviews are more useful. The lack of congruence could well result from the fact that some groups of consumers prefer to process positive reviews for decision making, while others focus more on negative reviews. In sum, recent research on consumer processing of online reviews suggests that consumers may pay attention to different information cues when evaluating online reviews.

3. Information Overload and Selective Information Processing in an Online Review Context

Online reviews are highly complex information bundles (Cheung and Thadani 2012) and processing them can be cumbersome for consumers who are trying to make sense of the plethora of available information. This has led to some consumers being confused or overwhelmed with the amount of information that they can use for their decision (Punj 2012; Park and Lee 2008). How can we expect consumers to react when facing such a large number of eWOM information cues on online review websites? Insights can be drawn from the comprehensive literature stream on information overload and information processing.

Research shows that situations in which the available information load is greater than the processing capacity pose a threat of information overload (Jacoby, Speller and Berning 1974; Savolainen 2007). While no single generally accepted definition of information overload exists, the term is usually taken to describe a situation in which an individual's efficiency in using information is impaired by the amount of potentially useful information available (Bawden and Robinson 2009; Eastlick, Feinberg and Trappey 1993). Because information overload increases the cognitive demand on consumers during information search, they turn towards heuristics that determine which information they attend to (Simon 1955). As a result, consumers opt for selective attention towards different informational cues within the decision environment (Payne and Bettman 2004). Such selective information processing allows them to take a decision while at the same time avoiding information overload. This outcome is usually achieved through the adaption of search strategies (Swain and Haka 2000), omission of certain information through selection (Bawden 2001) or reduced critical evaluation of available alternatives (Schultze and Vandenbosch 1998).

Research in this area focuses on strategies that consumers employ when choosing between different product alternatives, or between different product attributes (Jacoby, Speller and Berning 1974; Jacoby et al. 1987; for a detailed account, please refer to Payne and Bettman 2004). In this context, product attributes act as information cues that vary across different products. For example, when examining ready meals, a relevant information cue could be the amount of saturated fats, whereas when examining toothpaste, a completely different information cue, such as the presence of whitening agents, becomes relevant. For this reason, focusing on how consumers combine different information cues to form a pattern was not sensible due to the context-dependency of information cues. In contrast, the character of eWOM information cues is consistent across a large variety of online review websites and does not change from product to product. In other words, while the specific content of the information cues changes (e.g. the review text describing the product's performance), the way in which this information is displayed remains similar. Consumers therefore face a similar decision dilemma every time they process online reviews, namely which information to attend to In this paper, we extend prior literature by examining selective processing in terms of the specific combination of eWOM information cues.

A focal assumption underlying the information-processing approach is that individuals are able to develop and learn certain problem-solving strategies that may assist them in subsequent decision tasks. Consumers have knowledge about which strategy has worked in past decision situations and are likely to adopt the same strategy in a similar decision context (Bodenhausen and Wyer Jr. 1985). Drawing on this perspective, we theorize that consumers should be inclined to revert to familiar patterns when processing online reviews. Studies on online search behavior find that consumers tend to display repetitive patterns of website navigation in order to reduce cognitive effort (Johnson et al. 2004; Zauberman 2003). When visiting a website, consumers go through learning processes and become accustomed to certain features. When returning to this website, the user has a strong incentive to stick to these navigation patterns to minimize cognitive costs and facilitate an efficient decision-making process (Johnson et al. 2004). Transferring these insights to eWOM processing, we expect that repeating patterns of eWOM processing help consumers to reduce cognitive effort and arrive at an evaluation.

In spite of the growing relevance of online reviews to consumer decision-making, the overabundance of online reviews and subsequent reactions of consumers has been largely neglected in eWOM research. A notable exception is the work of Park and Lee (2008) who explicitly state that a large number of online reviews can lead to information overload. The authors propose that high involvement leads to active processing of online review content. They find that such content processing can quickly induce information overload when many reviews are present, which decreases purchase intention. Consumers with a low involvement level, however, use the number of reviews as a peripheral signal for product popularity without processing review content, and are thus not negatively affected by overload (Park and Lee 2008). While the work of Park and Lee (2008) is a first step towards examining the phenomenon of eWOM overload, it provides few insights regarding selective processing of different eWOM information cues. In turn, the authors' perspective differs from ours, both conceptually and empirically, in at least three ways. First, in contrast to Park and Lee (2008), we do not focus on general effects of overload on decision variables like purchase intention. Instead, we are interested in specific ways in which consumers actively reduce information load by selective processing. Rather than expecting that some consumers are at the mercy of information overload, we expect them to use selective processing patterns for decision-making – a view that is supported by the literature on information overload reduction (Payne and Bettman 2004). Second, we believe that Park and Lee's approach understates the number of information cues available on online review websites. For instance, they focus on positive reviews only. However, exposure to a solely positive review set is the exception rather than the norm. We focus on a larger number of information cues on online review websites to provide a more realistic picture. Third, while the paper of Park and Lee (2008) uses experimental research, we believe that we currently still lack fundamental insights on consumers' processing of eWOM information. Therefore, we employ an exploratory study and develop a measurement instrument.

4. Study 1 – Verbal Protocol Analysis

4.1 Methodology and Procedure

Study 1 is an exploratory study based on consumers' verbal "think aloud" protocols in situations of eWOM processing, which were complemented with in-depth follow-up interviews. The main goal of this approach is to investigate whether consumers indeed proceed strategically and selectively when processing eWOM information and whether they are aware of this behavior. Moreover, study 1 serves as a basis for subsequent quantitative analyses. This study helps us to extract relevant dimensions of selective eWOM processing, to identify factors that are related to this behavior, and to provide assistance with regard to grounded item generation for a sound measurement instrument.

During a verbal protocol procedure, participants are advised to think aloud while carrying out a decision task. A major advantage of verbal protocol procedures is that they help understanding how people solve problems and give the researcher access to respondents' sequence of thoughts while doing so (Ericsson and Simon 1984). The use of verbal protocols is particularly valuable when studying individuals' self-imposed behavioral rules (Hayes, Gifford and Hayes 1998), which makes this method appropriate for our purpose. In marketing research, verbal protocols are frequently employed in the context of exploring consumer decision-making processes (Biehal and Chakravarti 1982; Bolton 1993; Payne and Ragsdale 1978).

Participants were randomly assigned to evaluate either a digital picture frame or a hotel based on available information from two online review websites (*amazon.com* and *tripadvisor.com*). Those items were chosen as consumer electronics and hotels are frequently discussed categories in (e)WOM. In order to diminish bias due to prior experiences or preferences and make answers more comparable, we selected relatively unknown brands (a digital picture frame from *Intenso* and a hotel from the *Azimut* chain) and asked respondents to imagine advising a friend on whether to complete the purchase or not. Priming respondents for this specific task ensured that respondents met the situation with similar cognitive effort.

Specifically, even if respondents were not personally looking for a digital picture frame or a hotel they should contribute similar effort towards this decision when it concerns a friend (Bansal and Voyer 2000). Participants were only exposed to the online reviews of the digital picture frame on amazon.com, not to the general amazon.com website. The same procedure was used for the information on *tripadvisor.com*. The review information presented was identical for all participants, no new online reviews appeared on the respective websites during the time span of the study. For both conditions, the number of reviews was high ($N_{online\ reviews}$>100) and considerable variance within the online reviews was present, which ensured that the context of the task was both realistic and useful for studying the research question at hand. Participants were allowed to look at as much or as little eWOM information on the online review website as they wished and were asked to loudly articulate their thought and decision process. Apart from occasional reminders to "think aloud", the interviewer did not interfere with the process. The follow-up interview was used to deepen interesting insights from the respondent's decision task protocol. For instance, respondents were asked to revisit and summarize their strategy or highlight information cues on the website, which they perceived to be particularly important or unimportant for their decision making.

The sample consisted of 15 respondents (8 women and 7 men) who varied in age (16 to 65 years) and Internet experience and worked in a variety of occupations (e.g., student, entrepreneur, white-collar employee). All participants were familiar with online reviews and had used them for decision-making before. None of the participants were familiar with the picture frame brand or the hotel chain. The verbal protocols including the follow-up interviews lasted between 22 and 75 minutes. Protocol data was fully transcribed (8.5 hours, 55 single-spaced pages) and the researchers employed a thematic content analysis to the data (Braun and Clarke 2006; Spiggle 1994). Thematic content analysis is widely employed in psychology because of its ability to search for themes or patterns in otherwise relatively unstructured data without the application of prior theoretical dimensions. We extracted all statements related to the processing of eWOM information cues and grouped them into emerging themes for further analysis. Where necessary, diverging opinions on specific statements were resolved through discussion.

4.2 Results

The results revealed several essential insights. Most importantly, all participants in the study seemed to pursue intentional efforts to reduce information load on the respective online review website. As an example, one participant expressed *"(...) Well, I guess you could look at all available reviews, but seriously - who does that?"* Another person stated *"(...) you can never read everything on such a review site."* A third participant explained his approach with the words *"(...) when dealing with online reviews I don't proceed intuitively, but strategically. Methodically, as one might say."* Furthermore, all participants portrayed a selective processing procedure and focused on specific eWOM information cues while deliberately disregarding other cues. EWOM information cues included, for example, the number of reviews (e.g., 126 reviews), the titles of the reviews, the structure (e.g., use of bullet points, numbered lists of arguments) or shortness of the review text itself. For example, the element "online review text structure" was explicitly mentioned by a respondent in the following statement *"If it (the online review) is structured, you are able to see a common thread. That is maybe the most crucial aspect (...)"*, while another respondent commented on "shortness of online reviews" through the statement *"I find long online reviews annoying. I disregard those."*

Respondents generally appeared to be well aware of their selective processing patterns and had no difficulty in expressing them, both, in the verbal protocols and in the follow-up interviews. The majority of respondents seemed very certain about their typical processing patterns of eWOM information cues and many respondents claimed to *"always"* or *"never"* consider certain eWOM information cues, regardless of the purchase context. The following statement of the participant Carrie (22 years old, student), who evaluated the hotel chain based on information on *tripadvisor.com*, serves as a good example. She explained: *"(...) When I start looking at the reviews, I always look at the most negative reviews to get an idea about what is going wrong. (...) Also, I usually look at the very positive ones (...)."* Carrie also had a very decisive opinion on which aspects not to consider: *"I always skip the moderate [three star] ones, because you should really decide whether it [the hotel] is good or bad. Those airy-fairy reviews are of no use to me."* Of particular interest was the observation that several participants varied widely in the way they handled eWOM information. For example, consider the participant Barbara (25 years old, student), who focuses on different aspects than Carrie above: *"[First of all] the headline has to be interesting (...) like a short summary or already pointing out specific disadvantages (...) Then I look at reviews of five to ten lines, not longer. (...) You want to see quickly what was good or bad and not read some literary diffusions."*

In sum, these findings make us confident that consumers, under the condition of being at least somewhat familiar with online reviews and having relied on them for decision making before, (1) portray selective eWOM processing patterns in order to actively cope with information overload and (2) are cognitively aware of these patterns as well as able to adequately articulate them, even when being detached from the actual eWOM processing situation. Interestingly, this finding was consistent among respondents, regardless of how experienced the respondents claimed to be with online shopping or use of the Internet in general. Furthermore, we see indication that (3) variation regarding the way in which consumers handle eWOM exists. Lastly, (4) contextual factors seemed to play a subordinate role, as many participants reported a certain stability of their eWOM processing patterns across different situations. In turn, we are confident that it is possible to capture selective eWOM processing patterns through a psychometric measurement instrument.

5. Measurement of Selective eWOM Processing

5.1 Refinement of the Selective eWOM Processing Concept and its Dimensions

In order to extract all relevant eWOM information cues being processed by consumers, we used evidence from the protocol data. For instance, one of the verbal statements was *"what I always find extremely important is the title [of online reviews]"* (Barbara, 25, student), which we attributed to the eWOM information cue "online review title". Another respondent (Jake, 58, public servant) stated: *"(...) if he [the author] uses the same or a linguistic style related to my own style, the value of this online review does increase for me"*. From this statement we extracted the information cue "online review writing style". We compared these information cues to cues mentioned in relevant eWOM literature. We focused on articles that analyzed the role of different eWOM information cues in relation to online review processing. This ensured that we did not overlook any relevant information cues that have previously been discussed, but were not mentioned in the verbal protocols. Some of the eWOM information cues which were mentioned in the verbal protocols have also been investigated in prior eWOM literature, such as positive and negative online reviews (e.g. East, Hammond and Wright 2007; Purnawirawam, de Pelsmacker and Dens 2012) or helpfulness ratings of online reviews (e.g. Mudambi and Schuff 2010). Other eWOM information cues which were mentioned by the respondents have to our knowledge not been discussed in prior studies. We extracted four of such new cues, namely "online review title", "online review shortness", "online review text structure" and "argument quality". Results suggest 13 information cues that are important for selective eWOM processing. A detailed account of the 13 dimensions can be found in table 1.

[Table 1 goes about here]

The results from the verbal protocol data and the follow-up interviews revealed interesting insights on the dimensionality of the selective eWOM processing construct. In order to extrapolate the qualitative findings to a larger population of consumers and thus allow a more complete picture of the different forms of eWOM processing, we develop a multi-item measurement instrument. Our goal is to produce a parsimonious measurement instrument that includes only those items needed to explicitly measure the relevant dimensions (Gardner et al. 1998). While this can lead to lower reliability scores (Nunnally 1988), we believe that parsimony and conceptual clarity are to be favored over extensiveness when it comes to the applicability of measurement instruments in an online context. We use results from several different pretests, which build on the insights from our qualitative study and further serve to validate the dimensionality of the measurement of selective eWOM processing.

5.2 Initial Item Generation

We re-analyzed the verbal protocol and interview data and focused on statements that were concerned with expressions that explicitly show the ways in which consumers process different eWOM information cues to reduce information load in their information processing. This type of procedure has proven to be resourceful when building measurement items from qualitative data (Batra, Ahuvia and Bagozzi 2012). A typical statement that was extracted for this step was: *"You can't really read all of them, which is why I mainly focus on the positive ones."* Overall, we generated an initial item pool of 162 items.

Content Validity

Subsequently, content validity of the items was assessed by three academic experts who evaluated the items for clarity, understandability, and non-ambiguity in two separate discussion rounds. Additional to the list of items, experts were given the definition of selective eWOM processing as well as an explanation of the overall goal of the study. All items were rated on a scale from 1 to 5, where 1 equals a very low score on the respective quality criterion and 5 equals a very high score. All items with a mean score below 3 were discussed with the experts and considered for elimination. This led to a reduction of the initial item pool to 98 items (1st round) and 80 items (2nd round). Finally, 24 doctoral students in the marketing field allocated the items to the different dimensions identified in study 1 to provide an indication of whether the items were allocated to the intended information cues (Anderson and Gerbing 1991). This led to further elimination of 21 items and re-formulation of several items to enhance both meaningfulness and understandability (Churchill 1979).

5.3 Item Refinement and Pretest

The remaining 59 items were pretested with undergraduate students (n=105). The items were presented along with an introductory sentence *("In situations in which there is a very large number of online reviews for a product or service...").* This sentence served two specific purposes: (1) it ensured that all respondents were in a similar state of mind, in this case a situation, in which a large amount of reviews is present. The specific number of reviews that one understands as being large may vary individually and was therefore open for interpretation. (2) All items connected to the introductory sentence, which ensured a certain logical flow to the scale. Each page of the questionnaire also included an information graphic that displayed a typical review website, including relevant information cues. This made sure that all participants understood the wording in the items correctly and reduced potential biases from interpretation. Initial exploratory factor analysis and reliability checks as well as comments in the open question section at the end of the survey suggested some additional adjustments to the scale. The exploratory factor analysis revealed thirteen factors with an eigenvalue greater than one. In the following, we eliminated items with a factor loading below .5 (Hair et al. 2010) as well as well as items with a problematic cross-loading above .3. In addition, several participants commented on specific items which they found misleading or difficult to answer and on items they thought were clear and precise. We streamlined the number of items so that each factor was represented by two items in accordance with the participants' comments. Please see table 2 for a full account of all items.

6. Study 2 – Application to a Large Scale Consumer Survey

6.1 Method and Procedure

In order to collect data on the different selective eWOM processing patterns, we designed a survey. Respondents received a short overview of a typical online review website and were introduced to some basic terminology. Next, participants were asked to indicate the extent to which they agreed with the items designed to measure consumers' selective eWOM processing patterns (see table 2). Information from these items was used for subsequent segmentation of respondents into different selective eWOM processing types through cluster analysis.

Profiling Variables

We included four constructs as profiling variables for the emergent clusters to further detail our understanding about different types of eWOM processing patterns. Specifically, we included attitude towards online reviews, motives for reading online reviews, susceptibility to interpersonal influence, and Internet experience as profiling variables (please see the Appendix for an overview of all measurement items and reliability measures for the profiling variables). Prior research indicates that consumers' attitude towards online reviews can influence their reliance on online reviews for decision-making (Doh and Hwang 2009). Hence, we included four items adapted from Park and Kim (2008) to account for potential differences in consumer attitudes towards online reviews. Potentially, a negative attitude towards online reviews could lead consumers to focus on less informational cues, while a positive attitude could correspond with a strong focus on many informational cues. Research by Hennig-Thurau and Walsh (2003) shows that consumers differ in terms of their general motives for reading online reviews. Accounting for these motives may paint a better picture of potential reasons why a consumer might focus on certain information elements, but disregard others. Research has also shown that individuals react differently to advice from others because of their level of susceptibility to interpersonal influence (Bearden, Netemeyer and Teel 1989). As online reviews are by design a form of interpersonal influence in buying decision, we included four items to measure individual levels of susceptibility. Finally, we were interested in consumers' general experience with and opinion on the Internet. Consumers that think more positively about the Internet and are more proficient in using it might also exhibit different processing patterns.

6.2 Sample

We collected data using a sample from the online-panel *kjero.com*. The panel population consists of over two million product testers from Austria, Germany and Switzerland. The database is populated by consumers who have formally joined the platform via a sign-up process. Membership entitles the users to apply as product testers for different campaigns and provides them with access to numerous accounts of other product tests by fellow members. During such a campaign, consumers get to test the respective product, can obtain information about it and are encouraged to evaluate it. Respondents from this panel were deemed as especially valuable for an empirical investigation of the properties of the measurement instrument as they are confronted with online shopping, online reviews and product tests on a regular basis. Respondents were invited to take part in the online questionnaire via a personalized link and a short introduction to the topic on the panel website. As an incentive for participation, respondents were given the opportunity to participate in a prize raffle for one main prize and several product packages. The sample consisted of 2,732 respondents. After an initial screening question that asked respondents to indicate whether they had used online reviews for their decision making before, 2,606 respondents remained in the sample. We further excluded respondents with a survey response time below 6 minutes. This was deemed as too short a period to provide meaningful responses, as the median response time was approximately 10 minutes, resulting in a final sample of n=2,295 respondents (83.3% female; ⌀ age = 37.74). The large majority of respondents were employed (71.9%) and lived in a household with three

(24.4%) or four (27.1%) members. About half of the respondents were German (50.3%) and Austrian (42.6%), 7.1% were Swiss. Overall, respondents were well acquainted with the Internet, as 84.4% stated to go online several times a day.

6.3 Results from Exploratory and Confirmatory Factor Analysis

In order to assess the dimensionality of the data, the sample was randomly divided into two halves and the first half was subjected to an exploratory factor analysis (EFA). The Kaiser-Meyer-Olkin criterion (KMO) of .74 and the Barlett-test of sphericity ($p<.001$) indicated sufficient correlation in the data to warrant further interpretation of the factor structure through principal component analysis (PCA). Based on the Kaiser criterion, the initial factor solution revealed a 10-factor solution, with average variance extracted (AVE) of 72%. Varimax rotation of the items combined the two dimensions of “review text structure” and “author information”, which does not provide a meaningful and interpretable solution. While the Kaiser criterion is a useful indicator for the minimum number of factors in an item pool, it does not give meaningful advice on the most sensible factor structure from a theoretical standpoint (Stewart 1981), a fact that is especially relevant when evaluating measurement dimensions. Thus, we allowed for the extraction of an eleventh factor, which had an eigenvalue of .965 and was only slightly below the initial Kaiser criterion. This is in line with the reasoning that when the goal of an instrument is a meaningful depiction of the relevant measurement dimensions, extracting a slightly larger factor solution can be sensible (Stewart 1981). The 11-factor solution accounted for 75.7% of AVE, resulting in an increase of 3.2 %. The factor solution corresponded closely with our conceptually derived dimensions (for full description of all item texts, factor loadings and Cronbach’s α values, please see table 2).

[Table 2 goes about here]

The dimensions “review text structure” and “writing style” were combined into a meaningful new factor, which we label “online review structure and style”. However, two items that represented the dimension “star rating” did not display any clear loadings on one single factor but significant cross-loadings on several other factors. Therefore, this factor was deleted from further analysis. As three of the measurement dimensions include a direct reference to individuals’ behavior with regard to star ratings of a review (positive online reviews, negative online reviews, and moderate online reviews), this measure was deemed appropriate for the sake of a parsimonious and empirically sound measurement instrument without sacrificing the content rationale behind the measurement dimensions (Diamantopoulos 2005). The second randomly selected half of the data was subjected to confirmatory factor analysis (CFA) using AMOS version 22. The structural model including all 11 measurement constructs as well as covariance estimates between the constructs displayed good fit to the data (χ^2(df) = 1071.2(196), IFI = .957, CFI = .957, GFI = .962, RMSEA = .044, 90% confidence interval at [.042;.047], SRMR=.05), thereby indicating sound dimensionality and measurement properties of the confirmatory model (Steenkamp and van Trijp 1991). All item loadings were significant at $p<.01$ and above .6 except for one item for the construct that measured “shortness of online reviews” (.47). We considered deleting the item, however the factor loading was highly significant and a deletion would have resulted in a one-item measure. The significant item loadings as well as the respective standardized loading coefficients >.5 suggested that each of the items should remain part of the measurement model (Steenkamp and Van Trijp 1991). Average variance extracted for all factors exceeded the .5 threshold suggested by Hair et al. (2010). Together with acceptable construct reliability values (CR>.6), these results indicate sufficient convergent statistical validity of the model constructs, since all key measures of the measurement model’s construct validity are satisfactory (Hair et al. 2010).

Discriminant Validity and Common Method Bias

To further assess the discriminant validity of the factor structure, we conducted Fornell-Larcker tests for all possible factor pairs. The square root AVE exceeded the correlation estimate for all possible factor correlations (Fornell and Larcker 1981). Please see table 3 for a detailed account of all results. To investigate whether common method bias was an issue that necessitated further adjustment of the confirmatory model, we conducted Harman's single factor test and estimated a common latent factor model. Both tests did not reveal any evidence for common method bias, as Harman's single factor test resulted only in AVE of 21% for the forced single-factor solution and the common latent factor method did not reveal any differences above .2 between standardized regression estimates for both models (Podsakoff et al 2003), apart from the item that measured "shortness of online reviews". In sum, the analyses show reliable indication that the measurement instrument qualifies for further assessment of consumers' individual eWOM processing patterns.

[Table 3 goes about here]

Convergent Validity

We assessed convergent validity of our measurement instrument by re-using the verbal protocol data from study 1. If our measurement instrument is valid, participants of the verbal protocols (study 1) should portray consistent results with their verbal statements when filling out the items of the measurement instrument. All 15 participants of the verbal protocols (study 1) were re-contacted and asked to participate in a short survey, which included the 26 items for selective eWOM processing patterns. Respondents stated their name at the beginning of the survey, which later enabled us to match the survey results with the respective verbal protocol. N=12 completed questionnaires were returned. The time frame between this validation check and study 1 was large (> 1 year), hence reducing a potential bias from a carry-over effect. We cannot entirely rule out the possibility that selective eWOM processing patterns have changed in the time-span between the verbal protocols and this validation study (e.g., through having learned about certain features on online review websites). However, as the verbal protocols gave hints towards a rather consistent approach of dealing with eWOM information cues, we are confident that this does not constitute a problematic issue. A suspicion probe indicated that none of the respondents were aware of the connection of this survey to their prior participation in the verbal protocols. In order to compare the two data sources, two trained coders who were unaware of the research question read through the verbal protocols several times and identified statements that related to selective online review processing. Next, the coders rated each verbal protocol participant in terms of the eleven eWOM processing dimensions (from 1 = does not apply at all to 5 = fully applies) (e.g., a person who stated to always look at five star reviews in the verbal protocols would be rated by the coders as high on the dimension “positive online reviews”). We could therefore compare data from the verbal protocols (as rated by the coders) with survey data. The intra-class correlation coefficients ranged from .55 to .97, pointing towards a medium to strong level of agreement between the two raters (Hughes and Garrett 1990). We find significant correlations between the results of the survey and the verbal protocols (all $p<.1$). Correlation coefficients were high and ranged from .742 to .936, with the exception of three moderate correlations (ranging from .547 to .638). These results speak for convergent validity and give further indication that our measurement instrument is adequately able to capture eWOM processing types.

6.4 Results from Cluster Analysis

Cluster analysis was used on the full sample of study 2 in order to identify distinct types of selective eWOM processing patterns among respondents. We included the factor means for all eleven information dimensions as cluster variables. Next, we applied a two-step clustering approach by first utilizing hierarchical cluster analyses to determine the optimal number of clusters and then providing the initial cluster seed for a non-hierarchical clustering algorithm in a second step (Punj and Stewart 1983). Due to the large size of the sample, a random selection of several subsets of the data was analyzed separately in the hierarchical cluster analysis, using the Ward method and squared Euclidian distance (Cannon and Perrault 1999). We looked at different cluster solutions in order to determine a cluster solution that balanced both rigor and level of detail. Our goal was to ensure substantial differences between the clusters without artificially inflating the number of clusters. In addition, we wanted to establish a relatively equal distribution of individuals across all clusters. Therefore, we took into account changes in the agglomeration index as well as at the number of individuals per cluster. We decided between a three-cluster solution, which seemed a more rigorous solution, and a five-cluster solution, which would allow for a more detailed analysis of the differences between respondents with regard to their selective eWOM processing patterns. We decided for the more fine-grained five-cluster solution because we believe this provides more valuable results in terms of differences between respondents' selective processing patterns. The three-cluster solution entailed one very large cluster of N=1,039, as compared to the other two clusters of N=555 and N=701, which hampers a meaningful interpretation. Also, a more detailed cluster solution of more than five clusters did not result in a notable increase in the agglomeration coefficient (Grove, Fisk, and Dorsch 1998). We entered the cluster centroids of these five clusters as starting-seeds into a subsequent k-means cluster analysis. An ANOVA with cluster membership as the independent variable and the eleven eWOM information dimensions as dependent variables displayed significant differences on all eleven dimensions of eWOM information cues (see table 4). The five resulting clusters are described in the following.

[Table 4 goes about here]

Cluster 1 – The Efficients (N=504)

Respondents in this cluster put a strong emphasis on reviews that are short, timely, and helpful. Compared to other clusters, respondents also emphasize the use of headlines for review processing. This indicates that a typical cluster member wishes to retrieve information quickly and efficiently, without dedicating too much time and effort when attending to online reviews. Members mostly disregard information about the review author and the number of reviews and do not put specific emphasis on positive, negative or mediocre reviews. This cluster can be characterized as readers that deal with reviews in a time-efficient manner.

Cluster 2 – The Meticulous (N=382)

The Meticulous place importance on a variety of cues and portray a wish to derive in-depth information from online reviews. This cluster also puts a strong emphasis on content and quality of reviews. In relation to the other clusters, members also pay attention to a review's style and textual structure. Cluster members do not emphasize shortness of reviews, probably because those online reviews hold too little information for their needs. Their attention to various information cues indicates that these individuals value online review content highly.

Cluster 3 – The Quality-Evaluators (N=649)

Besides paying attention to online review recency and argument quality, members of this cluster portray a strong focus on information about the author of an online review. In addition, the helpfulness rating of online reviews seems to be an important cue for this user type. This indicates that cluster members particularly look out for quality signals when relying on online reviews for information search. They disregard mediocre reviews and do not pay special attention to positive reviews.

Cluster 4 – The Cautious Critics (N=419)

Members of this cluster focus strongly on the quality of arguments provided by online reviews and structure and style of the reviews, as indicated by the second highest mean across all clusters. In addition, negative reviews are very important for these users. It therefore appears that the cautious-critical user relies on online reviews to gain high-quality insights on what could go wrong with the purchase. In comparison, mediocre reviews that do not represent a clear-cut opinion are relatively unimportant, as displayed by the second lowest mean on that factor.

Cluster 5 – The Swift Pessimists (N=341)

Overall, these individuals seem to skim review content as displayed by the lowest mean values on the factors argument quality and style and structure. Their reliance on short reviews supports this view, as evidenced by the second highest mean score. In terms of valence, negative reviews are comparatively more relevant than positive or mediocre reviews, indicating that if reviews are consulted, this is mainly to get a quick overview on potential problems with a certain product.

Discussion of Profiling Variables

To further study the defining differences between the five clusters, we employed sequential multinomial logistic (ML) regression (Kleijnen, de Ruyter and Wetzels 2004) with cluster membership as the dependent variable and all profiling variables as the independent variables (Hosmer and Lemeshow 2000). For the ML, we used the Games and Howell (1976) procedure to maintain family-wise error rates for equal and unequal variances and equal and unequal sample sizes (Toothaker, 1992). The hypothesized model differs significantly from the intercept model, $\chi2(32)= 758.19$, $p<.001$, and showed adequate model fit in terms of the pseudo R^2 statistics (Cox and Snell's $R^2= .28$; Nagelkerke's $R^2= .29$). Inspecting the results of the likelihood ratio test statistic showed that all variables except opinion about the Internet contribute significantly to the explanatory power of the model with regard to cluster membership ($\chi2$ ranging from 20.16 to 65.55, $p<.001$, see table 4 for a detailed display of the mean values for all profiling variables).

Across all clusters, respondents' experience with and opinion of the Internet was high, with mean values ranging between 4.24 and 4.59. Respondents also exhibit a positive attitude towards eWOM. The strong reliance on a variety of eWOM information cues that is characteristic of cluster 3 (*The Meticulous*) is underlined by the highest means for susceptibility to interpersonal influence. Not only do these respondents make extensive use of eWOM, they are also aware of the influence others' opinion has on their decisions. On the contrary, respondents in cluster 5 (*The Swift-Pessimists*) think of themselves as least susceptible to interpersonal influence, which gives another indication of their skepticism. All respondents evaluate obtaining buying information and learning from other consumers as the most relevant motives for reading eWOM. Notably, respondents in cluster 1 (*The Efficients*) are not particularly interested in social interaction and do not seek community membership when reading eWOM. As these users seemed to use eWOM mostly as a quick and efficient way to gather relevant information this goes in line with their selective eWOM processing patterns.

7. General Discussion and Implications

This paper conceptualizes selective eWOM processing patterns, which we view as the combination of eWOM information cues processed by a consumer when looking for decision aids on online review websites. We gain exploratory insights from study 1, which shows compelling indication that consumers process eWOM information cues selectively and are easily able to articulate them in a confident manner. In order to investigate whether dominant types of eWOM processing patterns exist, we develop a quantitative measurement instrument based on the findings of Study 1. Several pretests and exploratory factor analysis result in 11 dimensions in form of eWOM information cues that can be relevant for selective eWOM processing. Empirical testing suggests convergent and discriminant validity of our construct and its measurement dimensions. We then apply the construct to a large-scale consumer panel. Our results suggest a typology of five prominent clusters of eWOM processing, namely *The Efficients, The Meticulous, The Quality-Evaluators, The Cautious Critics,* and *The Swift Pessimists* which we characterize through additional profiling variables.

Theoretical Contribution

From a theoretical perspective, our paper aims to make two key contributions to prior research. First, we contribute to information overload and information processing literature. Prior research has mainly examined outcomes of information overload and how consumers reduce product alternatives. Online review websites represent unique modern information environments, as website structure and available information cues are highly similar across different online review websites. This makes it interesting to examine the specific combination of information cues that a consumer processes, while deliberately disregarding other information cues as in order to reduce information load. By examining selective eWOM processing patterns, we extend an established research stream and apply it to a modern online environment. Second, we contribute to research on eWOM. While a large part of prior research in this field has advanced our understanding of the aggregate effects of online reviews on quantifiable outcomes such as sales, consumer processing of different eWOM information cues prior to this outcome is largely obscure. Our research extends first research of eWOM in connection to information overload (Park and Lee 2008) by examining selective processing of various eWOM information cues and by identifying prominent eWOM processing types. Our results indicate that eWOM processing is not a uniform endeavor but that the way in which consumers attend to eWOM information cues can be segmented into different clusters. Our paper also responds to calls for new insights into consumer behavior with regard to online reviews (Chevalier and Mayzlin 2006), as well as the incorporation of survey data to inform segmentation of consumers (MSI – Marketing Science Institute 2014).

Managerial Implications

In addition, important managerial implications can be derived from our findings. In light of the rising influence of eWOM on firm success, companies and website operators need a thorough knowledge of how consumers process online reviews. They are also eager to understand how online review websites should be designed and how consumer behavior with regards to this information source can be managed. As firm efforts to further develop online reviews as a marketing tool increase (Dellarocas 2003), knowledge about consumer processing of this complex information source becomes indispensable. Our results suggest that managing online review websites with a one-size-fits-all approach could neglect important differences, as different groups of consumers focus on different combinations of eWOM information cues. Firms can therefore integrate our measurement instrument to customer surveys to understand which eWOM processing type is dominant among their customers. Such insights help making online review behavior more predictable and offer distinct implications for managing firm responses to online reviews for the set-up of online review websites. Table 5 outlines specific managerial implications when dealing with the different processing types identified through our research. For instance, when a company finds that the majority of its customers consists of *Efficients,* the website operators should highlight eWOM information cues like short, timely, and helpful online reviews on the page. As *Efficients* primarily focus on these cues, such a website design would facilitate their information processing efforts. In contrast, when customers mainly consist of *Cautious Critics*, a company should pay special attention to employing adequate response strategies to negative reviews, which is the information cue that this group focuses on most. In doing so, companies can ensure that consumers who specifically use others' critique to make a decision can also see whether the company was able to address this critique. As this group of consumers also focuses on structure and style of online reviews, website operators could provide structure templates to eWOM writers.

[Table 5 goes about here]

How can a firm react if it does not deal with one predominant group of eWOM users but with several prominent clusters? In this case, a firm could enable sophisticated filtering mechanisms on the website. A firm could also strive for a personalization of online review website content (Jank and Kannan 2006). Considering that companies increasingly make use of retargeting strategies, personalization of online review websites would constitute a fruitful extension of already existing practices. The combination of eWOM information cues presented to a customer could be targeted based on survey results of the respective consumer. Properly addressing these challenges is vital for online retailer's success because reviews are powerful drivers of product conversion (Zhu and Zhang 2010).

8. Limitations and Further Research

Despite the contributions of our research, some limitations of our study as well as avenues for future research can be pointed out. Based on findings from study 1 as well as literature on repetitive online search behavior (e.g. Zauberman 2003) we are confident that eWOM processing patterns are relatively stable and do not change from situation to situation. Nevertheless, we cannot entirely eliminate the possibility that certain context variables, such as time pressure or product knowledge, do have an impact on eWOM processing patterns. Examining boundary conditions and moderators of selective eWOM processing patterns is therefore an important avenue for further research. For example, laboratory settings that expose respondents to on-screen search tasks and record search times under different conditions could shed further light on these issues. Such a controlled setting would enable clear evidence on how boundary conditions impact consumers' processing patterns.

Second, future work could expand our findings by focusing specifically on antecedents as well as outcomes of selective eWOM processing patterns. This may entail, for example, examining what factors are responsible for the formation of selective eWOM processing patterns (e.g. critical incidents like the first visit to an online review website). It would also be interesting to examine which type of eWOM processing pattern is most efficient in a given situation to derive at a decision, e.g., in terms of decision time, decision accuracy, or conversion rate. Third, study 2 draws on survey participants from a large online panel with considerably more female than male participants. Even though this arguably rather homogeneous group of respondents portrays distinct eWOM processing clusters, it would be interesting to apply the measurement instrument to a more heterogeneous sample of consumers, or conduct a cross-national study with eWOM users from various cultural backgrounds. Especially the investigation of cultural differences remains an important direction for further research. Fourth, future studies could cross-validate this measurement instrument by applying a thorough connection to visual measures such as eye tracking (Kuisma et al. 2010). Studying consumers' eye movements and website switching behavior while looking at online reviews could give important and interesting insights as to how websites should be modified to evaluate processing of online review information. Many consumers consult various information sources during their purchase journey and accounting for the interdependence between these information sources is an important avenue for future research issues. This would also enable the assessment of additional factors connected to the procedural character of eWOM processing, such as the processing order of certain information cues.

Appendix. Profiling Variables and Cronbach's α Values

Variables	***Items***	***Alpha***
Attitude towards Online Reviews	I always check consumer reviews before making a purchase I think consumer reviews are helpful Consumer reviews often influence my purchase decision I typically read consumer reviews before making a decision	.87
Motive: Obtaining Buyer-related Information	Because contributions by other customers help me to make the right buying decisions To benefit from others' experiences before I buy a good or use a service Because here I get information on the quality of products faster than elsewhere Because one saves a great deal of time during shopping when informing oneself on such sites before shopping	.76
Motive: Social Orientation Through Information	Because I can see if I am the only one who thinks of a product in a certain way Because I like to compare my own evaluation with that of others Because through reading one can get the confirmation that one made the right buying decision Because I feel much better when I read that I am not the only one who has a certain problem	.81
Motive: Community Membership	Because I am interested in what is new Because I enjoy participating in the experiences of other community members. Because I really like being part of such a community. Because I get to know which topics are "in."	.83
Motive: Remuneration	Because I get a reward for reading and evaluating contributions Because it allows me to earn a few Dollars	.93
Motive: Learning from Other Consumers	Because I find the right answers when I have difficulties with a product To find advice and solutions for my problems	.66
Susceptibility to Interpersonal Influence (Information Dimension)	To make sure I buy the right product or brand, I often observe what others are buying and using If I have little experience with a product, I often ask my friends about the product I often consult other people to help choose the best alternative available from a product class I frequently gather information from friends or family about a product before I buy	.83
Internet Expertise	*Using the Internet is….* Exciting vs. not exciting Important to me vs. not important to me Relevant to me vs. not relevant to me *I would describe the extent of my experience with the Internet as…* Extensive vs. not extensive	.68

Literature

Anderson, James C., and David W. Gerbing (1991), “Predicting the Performance of Measures in a Confirmatory Factor Analysis with a Pretest Assessment of their Substantive Validities”, *Journal of Applied Psychology*, 76, 5, 732-740.

Bansal, Harvir S., and Peter A. Voyer (2000), “Word-of-Mouth Processes Within a Service Purchase Decision Context”, *Journal of Service Research*, 3, 2, 166-177.

Batra Rajeev, Aaron Ahuvia, and Richard P. Bagozzi (2012), “Brand Love”, *Journal of Marketing,* 76, 2, 1-16.

Bawden David, and Lyn Robinson (2009), “The Dark Side of Information: Overload, Anxiety and other Paradoxes and Pathologies”, *Journal of Information Science,* 35, 2, 180-191.

Bawden, David (2001), “Information and Digital Literacies: a Review of Concepts”, *Journal of Documentation,* 57, 2, 218-259.

Bearden William O, Richard G. Netemeyer, and Jesse E. Teel (1989), “Measurement of Consumer Susceptibility to Interpersonal Influence”, *Journal of Consumer Research,* 15, 4, 473- 481.

Biehal, Gabriel, and Dipkanpar Chakravarti (1982), “Information-Presentation Format and Learning Goals as Determinants of Consumers’ Memory Retrieval and Choice Processes”, *Journal of Consumer Research,* 8, 4, 431-441.

Bodenhausen, Galen V., and Robert S. Wyer Jr. (1985), “Effects of Stereotypes in Decision Making and Information-Processing Strategies“, *Journal of Personality and Social Psychology*, 48, 2, 267-282.

Bolton, Ruth N. (1993), “Pretesting Questionnaires: Content Analyses of Respondents’ Concurrent Verbal Protocols”, *Marketing Science,* 12, 3, 280-303.

Braun, Virginia, and Victoria Clarke (2006), “Using Thematic Analysis in Psychology”, *Qualitative Research in Psychology,* 3, 2, 77-101.

Burke, Robin (2002), “Hybrid Recommender Systems: Survey and Experiments”, *User Modeling and User-Adapted Interaction,* 12, 4, 331-370.

Cannon, Joseph P., and William D. Perreault Jr. (1999), “Buyer-Seller Relationships in Business Markets”, *Journal of Marketing Research,* 36, 4, 439-460.

Cheung, Christy M. K., and Dimple R. Thadani (2012), “The Impact of Electronic Word-of-Mouth Communication: A Literature Analysis and Integrative Model”, *Decision Support Systems,* 54, 1, 461-470.

Chevalier Judith A., and Dina Mayzlin (2006), “The Effect of Word of Mouth on Sales: Online Book Reviews”, *Journal of Marketing Research,* 43, 3, 345-354.

Chrysanthos Dellarocas (2003), “The Digitization of Word of Mouth: Promise and Challenges of Online Feedback Mechanisms”, *Management Science*, 49, 10, 1407-1424.

Churchill, Gilbert A. Jr. (1979), “A Paradigm for Developing Better Measures of Marketing Constructs”, *Journal of Marketing Research,* 16, 1, 64-73.

Creyer, Elizabeth H., James R. Bettman, and John W. Payne (1990), "The Impact of Accuracy and Effort Feedback and Goals on Adaptive Decision Behavior", *Journal of Behavioral Decision Making*, 3, 1, 1-16.

Dellarocas, Chrysanthos, Xiaoquan (M.) Zhang, and Neveen F. Awad (2007), "Exploring the Value of Online Product Reviews in Forecasting Sales: The Case of Motion Pictures", *Journal of Interactive Marketing*, 21, 4, 23-45.

Deloitte (2014), "The Deloitte Consumer Review: The Growing Power of Consumers", A Deloitte Insight Report, available online at http://www2.deloitte.com/content/dam/Deloitte/uk/Documents/consumer-business/consumer-review-8-the-growing-power-of-consumers.pdf.

Diamantopoulos, Adamantios (2005), "The C-OAR-SE Procedure for Scale Development in Marketing: A Comment", *International Journal of Research in Marketing*, 22, 1, 1-9.

Doh, Sun-Jae, and Jang-Sun Hwang (2009), "How Consumers Evaluate eWOM Messages", *CyberPsychology & Behavior*, 12, 2, 193-197.

Duan, Wenjing, Bin Gu, and Andrew B. Whinston (2008), "Do Online Reviews Matter? An Empirical Investigation of Panel Data", *Decision Support Systems,* 45, 4, 1007-1016.

East, Robert, Kathy Hammond, and Malcolm Wright (2007), "The Relative Incidence of Positive and Negative Word of Mouth: A Multi-Category Study", *International Journal of Research in Marketing*, 24, 2, 175-184.

Eastlick, Mary Ann, Richard Feinberg and Charles Trappey (1993), "Information Overload in Mail Catalog Shopping. How Many Catalogs are too Many?", *Journal of Direct Marketing*, 7, 4, 14-19.

Ericsson K. Anders, and Herbert A. Simon (1984), *Protocol Analysis. Verbal Reports as Data*. Cambridge (MA): The MIT Press.

Fischer Peter, Stefan Schulz-Hardt, and Dieter Frey (2008), "Selective Exposure and Information Quantity: How Different Information Quantities Moderate Decision Makers' Preference for Consistent and Inconsistent Information", Journal of Personality and Social Psychology, 94, 2, 231–44.

Floyd, Kristopher, Ryan Freling, Saad Alhoqail, Hyun Young Cho, and Traci Freling (2014), "How Online Product Reviews Affect Retail Sales: A Meta-Analysis", *Journal of Retailing,* 90, 2, 217-232.

Fornell, Claes, and David F. Larcker (1981), "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error", *Journal of Marketing Research*, 18, 1, 39-50.

French, Tom, Laura LaBerge, and Paul Magill (2011), "We're all Marketers Now", McKinsey Quarterly, July 2011.

Games, Paul A., and James F. Howell (1976), "Pairwise Multiple Comparison Procedures with Unequal N's and/or Variances: A Monte Carlo Study", *Journal of Educational Statistics,* 1, 1, 113-125.

Gardner, Donald G., L. L. Cummings, Randall B. Dunham, and Jon Pierce (1998), “Single-Item Versus Multiple-Item Measurement Scales: An Empirical Comparison”, *Educational and Psychological Measurement,* 58, 6, 898-915.

Goldsmith, Ronald E., and David Horowitz (2006), “Measuring Motivations for Online Opinion Seeking”, *Journal of Interactive Advertising,* 6, 2, 3-14.

Grove, Stephens J., Raymond P. Fisk, and Michael J. Dorsch (1998), “Assessing the Theoretical Components of the Service Encounter: A Cluster Analysis Examination”, *The Service Industries Journal,* 18, 3, 116-34.

Hair, Joseph F., William C. Black, Barry J. Babin and Rolph E. Anderson (2010). *Multivariate Data Analysis. A Global Perspective*. Seventh edition, Upper Saddle River (NY): Pearson.

Häubl, G., & Trifts, V. (2000). “Consumer decision making in online shopping environments: The effects of interactive decision aids”. *Marketing Science* 19, 1, 4-21.

Hayes, Steven C., Elizabeth V. Gifford, and Gregory J. Hayes (1998), “Moral Behavior and the Development of Verbal Regulation”, *The Behavior Analyst,* 21, 2, 253-279.

Hennig-Thurau, Thorsten, and Gianfranco Walsh (2003), “Electronic Word-of-Mouth: Motives for and Consequences of Reading Customer Articulations on the Internet”, *International Journal of Electronic Commerce,* 8, 2, 51-74.

Herbert A. Simon (1955), “A Behavioral Model of Rational Choice”, *The Quarterly Journal of Economics*, 69, 1, 99-118.

Hosmer, David W., and Stanley Lemeshow (2000), *Applied Logistic Regression*. Second Edition, New York: Wiley.

Hughes, Marie A., and Dennis E. Garrett (1990), “Intercoder Reliability Estimation Approaches in Marketing: A Generalizability Theory Framework for Qualitative Data”, *Journal of Marketing Research*, 27, 2, 185-195.

Ipsos (2012), “Socialogue: Five Stars? Thumbs up? A+ or just average?”, *Ipsos Global @dvisor.* Retrieved 15.12.2014 from *http://www.ipsos-na.com/news-polls/pressrelease.aspx?id=5929*

Jacoby, Jacob (1977), “Information Load and Decision Quality: Some Contested Issues”, *Journal of Marketing Research*, 14, 4, 569-573.

Jacoby, Jacob, Donald E. Speller, and Carol K. Berning (1974), “Brand Choice Behavior as a Function of Information Load: Replication and Extension”, *Journal of Consumer Research*, 1, 1, 33-42.

Jacoby, Jacob, James Jaccard, Alfred Kuß, Tracy Troutman, and David Mazursky (1987), “New Directions in Behavioral Process Research: Implications for Social Psychology”, *Journal of Experimental Social Psychology,* 23, 2, 146-175.

Jank, Wolfgang, and P. K. Kannan (2006), „Dynamic E-Targeting Using Learning Spatial Choice Models“, *Journal of Interactive Marketing*, 20, 3-4, 30-42.

Johnson, Eric J., Woe, Wendy W., Fader, Peter S., Bellman, Steven & Lohse, Gerald L. (2004). On the depth and dynamics of online search behavior. Management Science, 50(3), 299-308.

King, Robert A., Pradeep Racherla, and Victoria D. Bush (2014), "What We Know and Don't Know About Online Word-of-Mouth: A Review and Synthesis of the Literature", *Journal of Interactive Marketing,* 28, 3, 167-183.

Kleijnen, Mirella, Ko de Ruyter, and Martin Wetzels (2004), „Consumer Adoption of Wireless Services: Discovering the Rules While Playing the Game", *Journal of Interactive Marketing*, 18, 2, 51-61.

Kronrod, Ann, and Shan Danziger (2013), ""Wii Will Rock You!" The Use and Effect of Figurative Language in Consumer Reviews of Hedonic and Utilitarian Consumption", *Journal of Consumer Research*, 40, 4, 726-739.

Kuan, Kevin K. Y., Kai-Lung Hui, Pattarawan Prasarnphanich, and Hok-Yin Lai (2015), "What Makes a Review Voted? An Empirical Investigation of Review Voting in Online Review Systems", *Journal of the Association for Information Systems*, 16, 1, 48-71.

Kuisma, Jarmo, Janaa Simola, Liisa Uusitalo and Anssi Öörni (2010), "The Effects of Animation and Format on the Perception and Memory of Online Advertising", *Journal of Interactive Marketing*, 24, 2, 269-282.

Libai, Barak, Ruth Bolton, Marnix S. Bügel, Ko de Ruyter, Oliver Götz, Hans Risselada, and Andrew T. Stephens (2010), "Customer-to-Customer Interactions: Broadening the Scope of Word of Mouth Research", *Journal of Service Research,* 13, 3, 267-282.

Liu, Yong (2006), "Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue", *Journal of Marketing,* 70, 3, 74-89.

MSI – Marketing Science Institute (2014), *2014-2016 Research Priorities*, Cambridge: MA.

Mudambi, Susan, and David Schuff (2010), "What Makes a Helpful Online Review? A Sudy of Customer Reviews on Amazon.com", *MIS Quarterly,* 34, 1, 185-200.

Nielsen (2012), "Global trust in advertising report", Retrieved 15.12.2014 from *http://www.nielsen.com/us/en/insights/news/2012/consumer-trust-in-online-social-and-mobile-advertising-grows.html*

Nunnally, Jum C. (1988) *Psychometric theory*. New York: McGraw Hill.

Pan, Yue, and Jason Q. Zhang (2011), "Born Unequal: A Study of the Helpfulness of User-Generated Product Reviews", *Journal of Retailing*, 73, 4, 598-612.

Park, Doh-Hyung, and Jumin Lee (2008), "eWOM Overload and its Effect on Consumer Behavioral Intention Depending on Consumer Involvement", *Electronic Commerce Research and Applications*, 7, 4, 386-398.

Payne, John W., and E. K. Easton Ragsdale (1978), "Verbal Protocols and Direct Observation of Supermarket Shopping Behavior: Some Findings and a Discussion of Methods", *Advances in Consumer Research,* 5, 1, 571-577.

Payne, John W., and James R. Bettman (2004), "Walking with the Scarecrow: The Information-processing Approach to Decision Research" in *Blackwell Handbook of Judgment and Decision Making,* Derek J. Koehler and Nigel Harvey, ed. Blackwell Publishing Ltd, 110-132

Payne, John W., James R. Bettman, and Eric J. Johnson (1988), "Adaptive Strategy Selection in Decision Making", *Journal of Experimental Psychology: Learning, Memory, and Cognition,* 14, 3, 534-552.

Podsakoff, Philip M., Scott B. MacKenzie, Jeong-Yeon Lee, and Nathan P. Podsakoff (2003), "Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies", *Journal of Applied Psychology*, 88, 5, 879-903.

Punj Girish, and David W. Stewart (1983), "Cluster Analysis in Marketing Research: Review and Suggestions for Application", *Journal of Marketing Research,* 20, 2, 134-148.

Punj, Girish (2012), "Consumer Decision Making on the Web: A Theoretical Analysis and Research Guidelines", *Psychology and Marketing,* 29, 10, 791-803.

Purnawirawan, Nathalia, Patrick de Pelsmacker, and Nathalie Dens (2012), "Balance and Sequence in Online Reviews: How Perceived Usefulness Affects Attitudes and Intentions", *Journal of Interactive Marketing*, 26, 4, 244-255.

Savolainen, Reijo (2007), "Filtering and Withdrawing: Strategies for Coping with Information Overload in Everyday Contexts", *Journal of Information Science,* 33, 5, 611-621.

Schultze, Ulrike, and Betty Vandenbosch (1998), "Information Overload in a Groupware Environment: Now You See it, Now You Don't", *Journal of Organizational Computing and Electronic Commerce,* 8, 2, 127-148.

Spiggle, Susan (1994), "Analysis and Interpretation of Qualitative Data in Consumer Research", *Journal of Consumer Research,* 21, 3, 491-503.

Steenkamp, Jan-Benedict E. M., and Hans C. M. van Trijp (1991), "The Use of LISREL in Validating Marketing Constructs", *International Journal of Research in Marketing*, 8, 4, 283-299.

Stewart, David W. (1981), "The Application and Misapplication of Factor Analysis in Marketing Research", *Journal of Marketing Research,* 18, 1, 51-62.

Swain, Monte R., and Susan F. Haka (2000), "Effects of Information Load on Capital Budgeting Decisions", *Behavioral Research in Accounting,* 12, 171-198.

Yin, Dezhi Yin, Samuel Bond, and Han Zhang (2014), "Anxious or Angry? Effects of Discrete Emotions on the Perceived Helpfulness of Online Reviews", *MIS Quarterly*, 38, 2, 539-560.

Zauberman, Gal (2003), "The Intertemporal Dynamics of Consumer Lock-In", *Journal of Consumer Research*, 30, 3, 405-419.

Zhu, Feng, and Xiaoquan Zhang (2010), "Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics", *Journal of Marketing,* 74, 2, 133-148.

Figure 1. Overview of the Research Process

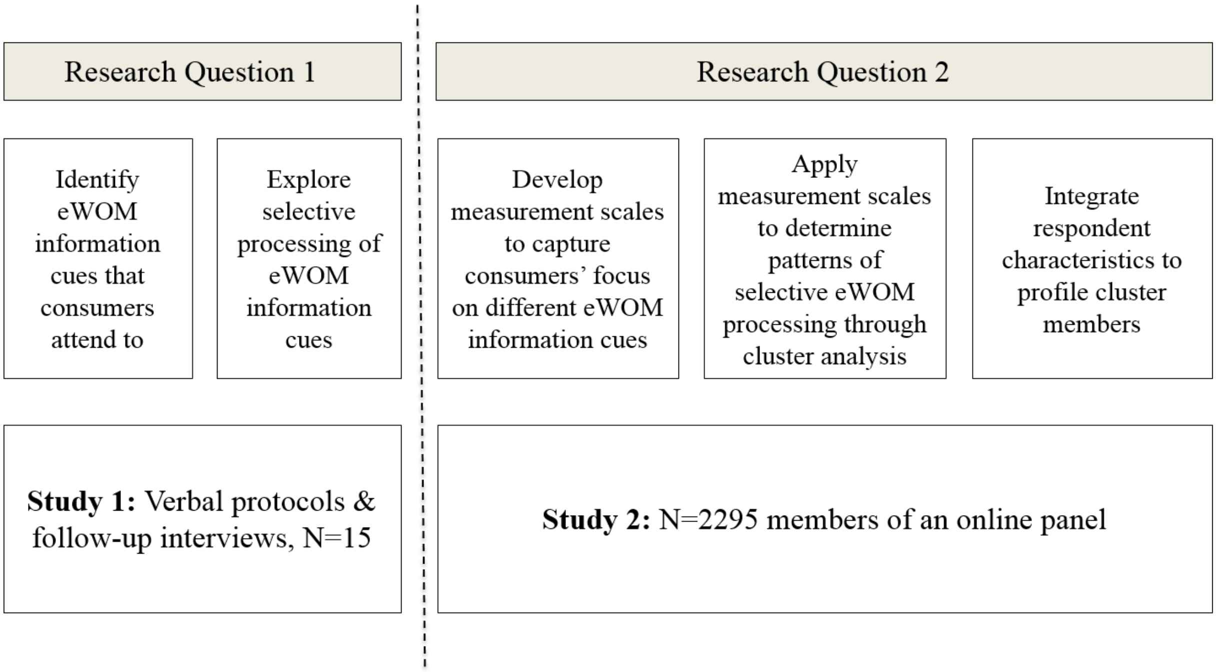

Figure 2. Exemplary eWOM Information Cues

Exemplary eWOM information cues on tripadvisor.com | *Exemplary eWOM information cues on amazon.com*

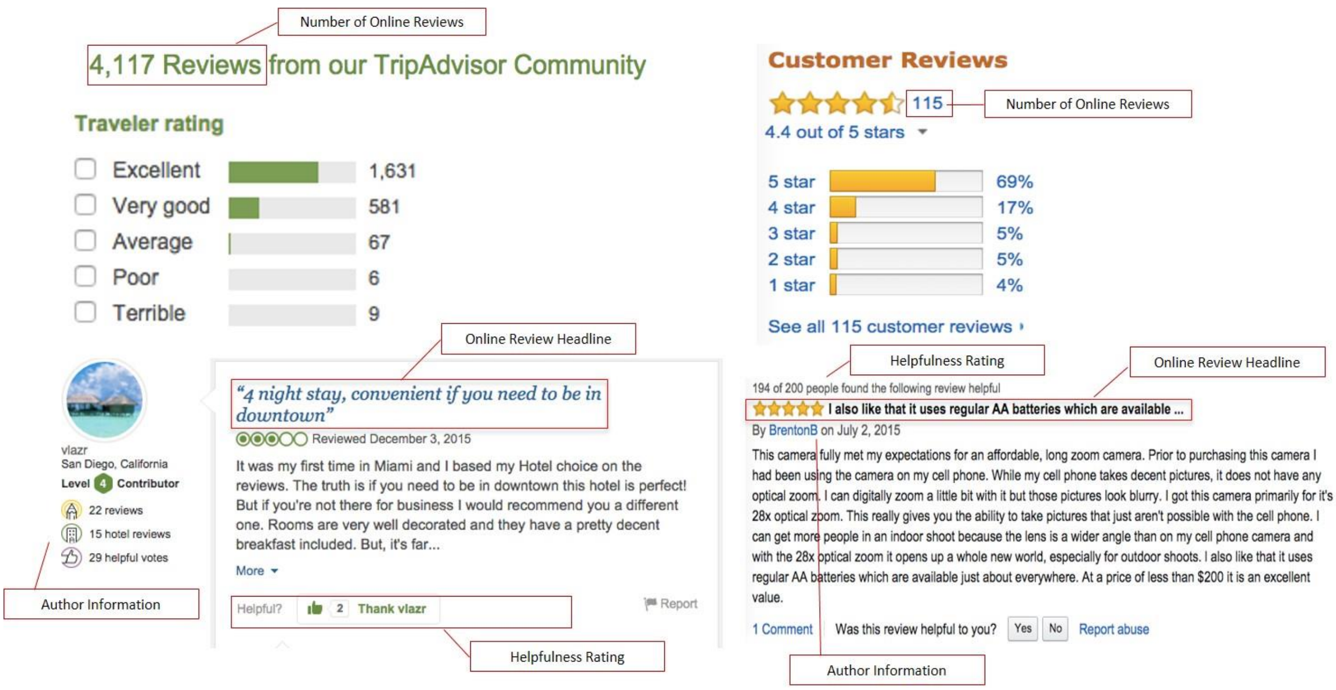

Table 1. Information Cues in Selective eWOM Processing

	Dimension	Description	Exemplary Quote from Verbal Protocols	Exemplary Evidence from Prior Literature
1	**Positive Online Reviews**	A focus on positive online reviews (e.g., 5 out of 5 stars)	*"[I pretty much only look at the positive ones (...)" (Lara, 27, employee)*	East, Hammond, Wright (2007) Purnawirawam et al. (2015)
2	**Negative Online Reviews**	A focus on negative online reviews (e.g., 1 out of 5 stars)	*"(...) I look at the one star reviews to understand what made them [the authors] evaluate [the product] so poorly." (Ed, 65, entrepreneur)*	East, Hammond, Wright (2007) Purnawirawam et al. (2015)
3	**Moderate Online Reviews**	A focus on moderate online reviews (e.g., 3 out of 5 stars)	*"I always skip the moderate ones, because you should really decide whether it [the hotel] is good or bad. Those airy-fairy reviews are of no use." (Carrie, 22, student)*	Mudambi & Schuff (2010)
4	**Online Review Recency**	A focus on whether online reviews were published recently	*"(...)online review content that is older than one year is not so relevant." (Kirsten, 31 research assistant)*	Cheung et al. (2008)
5	**Helpfulness Rating**	A focus on how helpful the online review has been rated by other consumers	*"I have never looked at whether a review was rated as helpful (by others) or not" (Gabby, 27, employee)*	Mudambi & Schuff, 2010 Baek, Anh, Choi, 2014
6	**Star Rating**	A focus on the number or distribution of stars	*"In general, I only look whether it [the product] has 5, 4, or 3 stars" (Jack, 58, public servant)*	Chevalier & Mayzlin, 2006
7	**Number of Online Reviews**	A focus on the overall number of available online reviews	*"227 reviews – that is already a good sign" (Marissa, 27, employee)*	Duan, Gu, & Winston, 2008
8	**Online Review Writing Style**	A focus on the linguistic writing style of the author of the online review	*„(...) if he [the author] uses the same or a related linguistic style to my own style, the value of this online review does increase for me" (Jerry, 58, public servant)*	Ludwig et al. (2013) Hamilton, Vohs, McGill (2014)
9	**Author Information**	A focus on information about the author of the online review (e.g., personal information, amount of prior reviews written)	*"What is often interesting is to look at how many reviews the people have written before." (Kirsten, 30, research assistant)*	Forman, Ghose, & Wiesenfeld, 2008
10	**Online Review Shortness**	A focus on short online reviews	*"I find long online reviews annoying. I disregard those" (Barbara, 25, student)*	-
11	**Online Review Text Structure**	A focus on whether the online review text is logically structured	*„ If it (the online review) is structured, you are able to see a common thread. That is maybe the most crucial aspect. The logical structuring of such as review, that is important." (Irene, 18, high school student)*	-
12	**Argument Quality**	A focus on whether arguments presented in the online review text are meaningful	*„It is important to me that [the author] tries to convey subjectivity. The content has to be substantive" (Daniela, 56, self-employed)*	-
13	**Online Review Title**	A focus on the title or headline of online reviews	*"What I always find extremely important is the title [of online reviews] because you get much information out of them" (Carrie, 22, student)*	-

Table 2. Factor Loadings and Cronbach's α Values

Factor	*Item Wording* *In situations where there is a very large number of online reviews about a certain product or service available...*	*Factor Loading*	*Alpha*
(1) Online Review Structure and Style	…I give less weight to an online review with linguistic mistakes (grammar, style)	.769	.720
	…I focus on the online review author's writing style	.747	
	…I mostly read online reviews where the text is clearly structured	.630	
	…I attribute less importance to an online review if the text is not divided into paragraphs	.622	
(2) Positive Online Reviews	… those online-reviews, which emphasize positive aspects of the product or service, are especially relevant to my decision	.827	.766
	… I focus on positive online-reviews (e.g., 5 out of 5 stars)	.807	
(3) Negative Online Reviews	… I focus on negative online-reviews (e.g., 1 out of 5 stars)	.895	.871
	… those online-reviews, which emphasize negative aspects of the product or service, are especially relevant to my decision.	.892	
(4) Helpfulness Rating	… I mainly focus on the number of other people who rated an online review as „helpful"	.899	.901
	… I select and read those online reviews that were rated as particularly helpful by other readers	.897	
(5) Number of Online Reviews	…I particularly pay attention to the overall number of people who have reviewed a specific product	.879	.855
	…I find the available number of online reviews for a specific product (e.g., 300 online reviews) especially relevant	.868	
(6) Argument Quality	…In my decision-making, I give particular weight to objective, factual online reviews	.770	.724
	…I focus on evaluating whether the statements within an online review are appropriately justified	.768	
(7) Online Review Recency	… I primarily read those online reviews that were posted recently	.907	.845
	… I pay special attention to the date on which the online review was posted	.898	
(8) Author Information	…I give a lot of weight to online reviews in which the author provides information about himself and his personal preferences.	.875	.829
	…I particularly pay attention to those online reviews that provide information about the reviewer (name, picture, number of online reviews written)	.858	
(9) Online Review Title	…I mainly try to get a summary of the content by looking at the titles of online reviews.	.885	.822
	… I mostly consider the title of online reviews	.873	
(10) Moderate Online Reviews	… those online-reviews, in which neither positive nor negative aspects about the product or service dominate, are especially relevant to my decision	.826	.700
	… I focus on moderate online-reviews (e.g., 3 out of 5 stars)	.810	
(11) Online Review Shortness	…I prefer reading online reviews that are kept short	.841	.501
	…I mainly read long, detailed online reviews (reverse coded)	-.772	

Table 3. Factor Reliability and Discriminant Validity

Factor	CR	AVE	Online Review Title	Positive Online Reviews	Moderate Online Reviews	Online Review Shortness	Helpfulness Rating	Author Information	Argument Quality	Number of Online Reviews	Negative Online Reviews	Online Review Structure and Style	Online Review Recency
Online Review Title	.815	.688	.830[1]										
Positive Online Reviews	.737	.584	.302[2]	.764									
Moderate Online Reviews	.680	.516	.266	.207	.718								
Online Review Shortness	.640	.527	-.020	-.169	-.249	.726							
Helpfulness Rating	.900	.818	.318	.280	.279	-.133	.905						
Author Information	.829	.708	.273	.171	.372	-.242	.355	.842					
Argument Quality	.711	.551	.214	.175	.142	-.324	.215	.205	.743				
Number of Online Reviews	.847	.734	.287	.315	.315	-.315	.275	.354	.332	.857			
Negative Online Reviews	.865	.763	.118	.030	.216	-.218	.009	.071	.276	.145	.873		
Online Review Structure and Style	.713	.537	.305	.203	.275	-.234	.329	.418	.425	.321	.143	.733	
Online Review Recency	.841	.726	.284	.180	.248	-.096	.260	.275	.296	.286	.066	.250	.852

[1]The numbers on the diagonal represent the square root AVE of each construct.

[2]Numbers below the diagonal depict the correlation of each factor with all other factors.

Table 4. Results from Cluster Analysis and Profiling Analysis

Cluster Variables	The Efficients (A)	The Meticulous (B)	The Quality-Evaluators (C)	The Cautious Critics (D)	The Swift Pessimists (E)	*F*(4,2292)	*p*
Positive Reviews	3.26^{D}	3.88	2.94	3.17^{A}	2.53	125.07	.000
Negative Reviews	3.19^{E}	3.82	3.46	3.77	3.13^{A}	42.69	.000
Moderate Online Reviews	2.28^{D}	3.37	2.69	2.29^{A}	2.02	158.44	.000
Online Review Recency	3.74	4.30	3.54^{D}	3.51^{C}	2.65	142.29	.000
Online Review Title	3.51	3.93	2.94	2.72	2.19	235.82	.000
Number of Online Reviews	2.74	3.92	3.16^{D}	3.02^{C}	2.05	206.26	.000
Argument Quality	3.79^{C}	4.32	3.84^{A}	4.29	2.93	250.12	.000
Helpfulness Rating	3.27	4.09	3.09	2.71	2.09	225.23	.000
Author Information	2.33	3.92	3.47	1.73	1.92	785.39	.000
Online Review Shortness	4.09	3.17^{E}	2.82	2.63	3.21^{B}	320.89	.000
Online Review Structure and Style	$3.02^{C,D}$	3.69	3.12^{A}	2.88^{A}	2.20	183.75	.000
Attitude Towards Online Reviews	3.56	3.99^{D}	3.74	3.92^{B}	3.35	36.68	.000
Susceptibility to Interpersonal Influence	$3.22^{C,D}$	3.83	$3.27^{A,D}$	$3.12^{A,C}$	2.74	66.93	.000
Internet Expertise	$4.33^{C,E}$	4.59	$4.40^{A,D}$	4.45^{C}	4.24^{A}	20.99	.000
Motive: Obtaining Buying-related Information	3.88^{C}	4.31	3.87^{A}	4.03	3.45	82.82	.000
Motive: Social Interaction	$3.17^{C,D}$	3.89	3.26^{A}	3.08^{A}	2.59	96.09	.000
Motive:Community Membership	2.96^{D}	3.76	3.13	2.95^{A}	2.48	93.48	.000
Motive: Remuneration	1.69	2.33	1.88^{E}	1.41^{D}	1.42	49.79	.000
Motive: Learning From Other Consumers	$3.36^{C,D}$	4.04	3.49^{A}	3.31^{A}	2.85	73.11	.000

Notes: Superscripts indicate no statistically significant differences at $p<.05$ between the respective clusters, all other differences are significant at $p<.05$.

Table 5. Cluster Summary and Managerial Implications

Cluster	Cluster Characteristics	Managerial Implications
1. *The Efficients*	Particular focus on short online reviews that are timely and rated as helpful	• Display recently published reviews that were rated as helpful at the top of the page • Introduce character limits for online reviews • Pay special attention to efficient website design
2. *The Meticulous*	Strong focus on all review characteristics, in particular to quality of content. Lowest focus on online review shortness	• Introduce minimum length restrictions for online review texts • Provide a large number of eWOM information cues on the website and enable readers to make their own selection of filters • Close monitoring of eWOM activities, as it seems to be a crucial pre-purchase information source for this user
3. *The Quality-Evaluators*	Focus on author information, argument quality, and helpfulness	• Introduce mandatory provision of author information for online review writers, such as real names or location • Pay special attention to the quality appeal of the online review website, e.g. by giving reviewer authors tips for good review writing • Implement additional quality signals, such as "verified purchase" of a product
4. *The Cautious Critics*	Focus on high-quality, negative content as well as structure and style of reviews	• Stress adequate firm responses to negative online reviews • Enhance structure and style of online reviews by providing structure templates to eWOM writers
5. *The Swift Pessimists*	Focus on short and negative online reviews	• Providing personalized solutions for this cluster does not appear to be profitable, as this user type displays overall low focus on eWOM information cues and rate low on susceptibility to interpersonal influence • At most, a light monitoring approach of negative eWOM seems feasible