

NOT ALL REVIEWS ARE EQUAL - A LITERATURE REVIEW ON ONLINE REVIEW HELPFULNESS

Research paper

Rietsche, Roman, University of St.Gallen, St.Gallen, Switzerland, roman.rietsche@unisg.ch
Frei, Daniel, University of St.Gallen, St.Gallen, Switzerland, daniel.frei@student.unisg.ch
Stöckli, Emanuel, University of St.Gallen, St.Gallen, Switzerland, emanuel.stoeckli@unisg.ch
Söllner, Matthias, University of St.Gallen, St.Gallen, Switzerland, matthias.soellner@unisg.ch
& University of Kassel, Kassel, Germany, soellner@uni-kassel.de

Abstract

The amount of online reviews is growing significantly. Between 2014 and 2017, the number of reviews for TripAdvisor grew by 300% and for Yelp by 208%. However, not all online reviews are equally valuable. Some reviews are perceived to be more helpful or trustworthy than others. Hence, plethora of scholars have investigated the role of online reviews and researched factors and characteristics determining its helpfulness. Nevertheless, mixed findings were found. Consequently, the purpose of our paper is to present a holistic and representative analysis of the literature on factors indicating the helpfulness of online reviews. In total, we analyzed 81 journal articles and inductively created a framework resulting in four dimensions: review-related factors, reviewer-related factors, reader related factors and environment-related factors. The results revealed that researchers mainly focused on factors of the first two dimensions and that the findings are inconsistent and need to be further researched in the future.

Keywords: online reviews, review helpfulness, literature review, research agenda, co-topic analysis.

1 Introduction

The amount of online reviews is growing significantly. In only three years from 2014 to 2017 the number of reviews on TripAdvisor grew by 300%, to 600 million reviews in total (TripAdvisor, 2018). In the same period the amount of reviews on Yelp grew by 208% to 148 million in total (Yelp, 2018), and statistics are similar for other platforms. One of the factors causing this increase is the fact that reviews are well-established reputation mechanisms to encourage trust in markets with asymmetric information (Resnick and Zeckhauser, 2002).

However, not all online reviews are equally valuable. Some reviews are perceived to be more helpful or trustworthy than others. Hence, a plethora of scholars have investigated the role of online reviews and researched factors and characteristics determining its helpfulness (Ba and Pavlou, 2002; Pavlou and Gefen, 2004; Lauterbach *et al.*, 2009). However, not only providers (sellers, service providers, etc.) and consumers (buyers, customers, etc.) of online platforms such as Yelp, TripAdvisor, Amazon etc., but also participants in a sharing society are exposed to risks due to asymmetric information. Hence, the well-established mechanism of online reviews is also used in sharing society (Fradkin *et al.*, 2018). Therefore, this paper analyses the body of literature of online platforms, to transfer knowledge to the sharing society body of literature (Lauterbach *et al.*, 2009; Ert *et al.*, 2016). However, existing literature that has investigated aspects of online reviews reveals mixed results. For example, it is not clear whether longer or shorter reviews (text length) are more helpful. Filieri (2016) argues that shortness indicates a fake review while Kwok and Xie (2016) argue that shorter reviews are more helpful because they are more readable. Similar mixed findings can be found in the sharing society body of literature. Ross *et al.* (2018) compared two different designs of warning messages on social media to detect fake news and found that none of the two designs is clearly superior although previous studies suggest that a more

complex design would be more likely to be effective. Hence, without a structured analysis and consolidation of critical factors of review helpfulness in online platforms, it is difficult to transfer and adapt this knowledge to the sharing society.

Online reviews are often unstructured and need to be analyzed by sellers and buyers (Aggarwal, 2016). For sellers, the problem is that a bad online reputation can rapidly lead to a great slump in revenue (Chen *et al.*, 2004). Due to the limited options to identify harmful reviews right at the time when they are posted, the only possibility for sellers is to respond to negative reviews in retrospect. However, in this case the damage to the business oftentimes already happened before a seller even noticed the review.

For buyers, reviews are the key source to inform their purchase decision. By the end of the year 2015, about 70% of people were searching for reviews on Yelp via a mobile device (Rubin, 2016). However, the massive amount of reviews leads to information overload (Salehan and Kim, 2016). In the sharing society of today's digital age, a great amount of online reviews is generated every second. The production speed and volume of new reviews is prompting buyers and sellers. Different filter options and voting systems are used to identify and display the most helpful reviews (Cao *et al.*, 2011). However, according to Min and Park (2012), most of these systems fail because of early bird bias. The most helpful review might only be the most helpful review among early posted reviews because most people limit their review research to reading the top-rated reviews (Lee, 2013). Therefore, early posted reviews that were voted as helpful get much more attention than subsequently posted reviews (Lee, 2013), independent of the actual helpfulness of their content.

Consequently, the research question of this paper is: What are the factors determining review helpfulness in online platforms? Therefore, we present a holistic and representative analysis of the literature on factors indicating the helpfulness of online reviews. Following the approach according Webster and Watson (2002) and vom Brocke *et al.* (2015) overall, 81 journal articles were analyzed in depth. The analysis reveals that the two most searched factors for review helpfulness are a) ratings, which is a review-related factor, and b) reputation, which is a reviewer-related factor. Both factors are investigated together in one quarter of the analyzed journal articles. For the presentation of our findings, we introduce a new visualization method we call co-topic analysis. Best to our knowledge we are the first researchers using this type of visualization.

This paper contributes to both theory and practice alike. We contribute to theory, by inductively creating a theoretical framework trying to understand the context of online reviews, their factors and characteristics. Furthermore, through the application of review-related, reviewer-related, reader-related and environment-related factors, we offer a conceptualization of what and in which dimension the factor contributes to the perceived helpfulness of an online review. Moreover, we developed a new visual representation form to present analyzed topics in a structured literature reviews. We contribute to practice by providing insights in how to design a review system, guiding reviewers to write helpful reviews and new ways of how to display the most helpful reviews.

The paper is structured as follows, section two deals with the theoretic background. Key terms and concepts, which are relevant to this field, will be explained. In section three, a description of the review process is provided. Section four presents the findings of the review process on both a descriptive and thematic level. In section five the findings are discussed. Finally, section six puts forward an overall conclusion.

2 Theoretical Background

Online reviews are “a type of product information created by users based on personal usage experience which can serve as [information] to help consumers identify the products that best match their idiosyncratic usage conditions” (Chen and Xie, 2008). Review helpfulness is defined as the extent to which the customer perceives that a review helps making the right decision in the purchasing process (Mudambi and Schuff, 2010). Voting systems and filter options are two systems that are used nowadays to identify helpful reviews (Cao *et al.*, 2011). Either the voting system asks the reader to rate a review as helpful or

not helpful or it simply works with up- and down-votes. Different filter options are available to show for example the most recent or most helpful reviews (reviews with most positive votes).

Many researchers of online review helpfulness differentiate between two product types a) search goods and b) experience goods. Search goods can be generally described as products of which the characteristics can quite easily be evaluated before purchasing them (Luan *et al.*, 2016). Experience goods can be generally described as products of which the characteristics are quite difficult to evaluate prior to buying them (Baek *et al.*, 2013). It is very important to differentiate between the two types of products because the product type influences the effect of some factors on the helpfulness.

Besides the differentiation between product types, it is important to understand the concept of the negativity bias. This concept deals with the psychological effect of negative versus positive information. According to the negativity bias, the effect of negative information is much stronger than the effect of positive information. A great example for the negativity bias is the damage to VW's reputation after the emissions scandal in 2015 (Neat, 2015). The negative information outweighs the positive information, because negative information reveals more about the personality and character of someone than positive information does (Wu, 2013).

To classify the literature, we built on the framework by Liu and Park (2015) and Yang *et al.* (2017b) and inductively altered it based on the findings of our literature analysis. Whereby the components of our framework reflect the general understanding of information exchange, which includes the actor A and B, the information to be exchanged and the environment. Yang *et al.* (2017b) explicitly used the terms "reviewer-related attributes" and "review-related attributes". We extended this framework with the reader-related factors and environment-related factors. Hence, the framework consists of four dimensions: 1) review-related factors, 2) reviewer-related factors, 3) reader-related factors and 4) environment-related factors. During the literature search process, the literature was clustered according to this framework. The individual factors are introduced subsequently.

The first dimension contains review-related factors. This includes all aspects which are related to the review itself, hence the content, structure and value (what information is exchanged). Consistency measures to what extent a review is similar or different to other reviews for the same product (Cheung *et al.*, 2012). The factor images represents all visual information added to a review (Yang *et al.*, 2017b). Persuasiveness includes different measures such as emotions in the text or the quality of the arguments (Fang *et al.*, 2016). Posting time includes all time measurements (Fang *et al.*, 2016). Reference measures to what extent a review is referring to other reviews or products (Weathers *et al.*, 2015). Rating subsumes all factors in relation to numerical or star rating (Cheung *et al.*, 2012). Depth measures the amount of information in the review by analyzing the number of sentences, words or characters (Guo and Zhou, 2017). Readability measures the ease of reading a review with the help of readability tests (e.g. Gunning-Fog index, Flesch-Kincaid reading ease, automated readability index, Coleman-Liau index) (Korfiatis *et al.*, 2012).

The second, dimension contains the reviewer-related factors. This is defined as factors, which are directly related to the person providing the review, hence the characteristics of the person as well as previous actions (who is the actor sending information). Information disclosure includes all information available about the reviewer such as location, profile picture, age, gender etc. (Gao *et al.*, 2017). Reputation measures the extent to which a reviewer is perceived to be an expert and credible, hence the total number of reviews written, the social status on the platform etc. (Cheung *et al.*, 2012).

The third, dimension contains the reader-related factors. This dimension contains all factors, which are related to the person who receives the review. Hence, the psychological condition of the reader, as well as how the reader responds to the review (who is the actor receiving information). The psychological factors include all internal influences on the perception of the reviews, such as risk aversion and search strategy (Li *et al.*, 2017). Identification measures to what extent the reader identifies him-/herself with the review environment and the reviewer (Davis and Agrawal, 2018).

The fourth and last dimension contains the environment-related factors. This dimension contains all factors of how and where the reviews are provided from the reviewer to the reviewee (how and in which environment is the information exchanged). Visibility measures to what extent the review is/was visible

to the readers, such as total number of available reviews (Hu and Chen, 2016). Voting measures the influence of a voting system on the perception of the reviews (Kuan *et al.*, 2015). Social network integration measures what effect the integration of social networks (e.g. Facebook) have on the online review helpfulness (Huang *et al.*, 2017). Response deals with the effect of responses to a review on the helpfulness (Ryang *et al.*, 2015). The website factor captures the influence of the website on which the review was posted, hence the reputation (Kim *et al.*, 2017).

3 Methodology

We conducted a structured literature review using the approach of Webster and Watson (2002) and vom Brocke *et al.* (2015). The first step of the literature search process included the development of the search string (see Figure 1), which was used for the search in the three databases: a) AISeL, b) ProQuest and c) EBSCOhost. To increase the hit rate, synonyms for all key words were included in the search string. The search was restricted to journal articles published in the years 2011 to 2018 (July 21st) and to abstract only because all relevant journal articles use these key words in the abstract. The period was chosen because in the years before, journal articles were only published occasionally. In total, 392 journal articles were found in the three databases, which were chosen because they focus on literature about information systems. The greatest part conducted an analysis of publicly available data collected from various review websites. Amazon is the most prominent data source for analysis (35%). Second most used review platform is Yelp (15%), followed by TripAdvisor (10%).

The second step included the definition of selection criteria. Only journal articles were selected for the final analysis, which were published in a journal with a 2017 Journal Impact Factor (JIF)/2017 CiteScore over 1.0. JIF values are provided by Thomson Reuters (Reuters, 2017) and the CiteScores (Scopus, 2017). The JIF score was used because it is a well-established measure for the relevance of journals. The CiteScore was added because not all journals were found on Thomson Reuters and in this case, the CiteScore was used as a substitute. Additionally, only journal articles which included qualitative or quantitative data collection were used for the final analysis. The screening and selecting process left 45 of the initial 392 journal articles for further analysis. These 45 journal articles were then used for a backward search as proposed by Webster and Watson (2002). In total 871 sources were screened and selected during the backward search. The same criteria were used as for the initial search. Regarding the publication year, one exception was made for Mudambi and Schuff (2010) because this paper is fundamental for this research field and many of the following researchers cited this paper. Finally, 36 new journal articles were added to the initial 45 resulting in a total of 81 journal articles. For the final analysis, a framework with four dimensions was inductively created based on the findings in the literature.

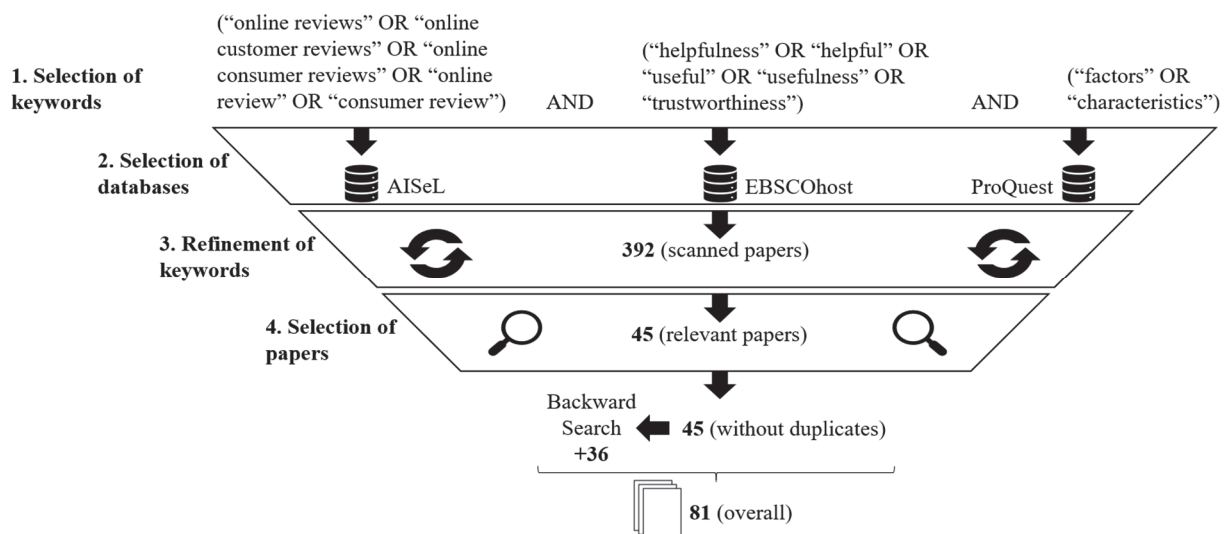


Figure 1. Literature search process based on the approach of Webster and Watson (2002) and vom Brocke *et al.* (2015)

For presenting the results, we developed a new method called co-topic analysis, which is based on the concept matrix proposed by Webster and Watson (2002). The idea of this method is to provide a holistic and compact overview of topics researched in scientific articles and more importantly their intra- and interrelationship. Co-topic analysis has the advantage over the approach of tables, of visualizing the most important information using a small amount of space. A visualization makes it easier for the reader to absorb the information. The method uses a hierarchical approach including dimensions which are at the first level an aggregation of 1:n topics, at the second level the topics and at the third level the sub-topics. The co-topic analysis provides the reader insights into four important questions: 1) How many topics are researched in total. Hence, which of the factors are researched in which paper, which is shown by the small reference number for each sub-factor. 2) What are sub-topics and how often are they researched. Thus, the reader is easily able to identify the importance of dimensions and topics by considering the bubble sizes including the number of papers researching this topic. 3) How many papers researched a topic/sub-topic and 4) How many papers are researching the same topic. The reader is able to identify the factors, which are most frequently researched together, which is showed by the arrows between the sub-factors including the number of papers investigating this factor together.

4 Findings

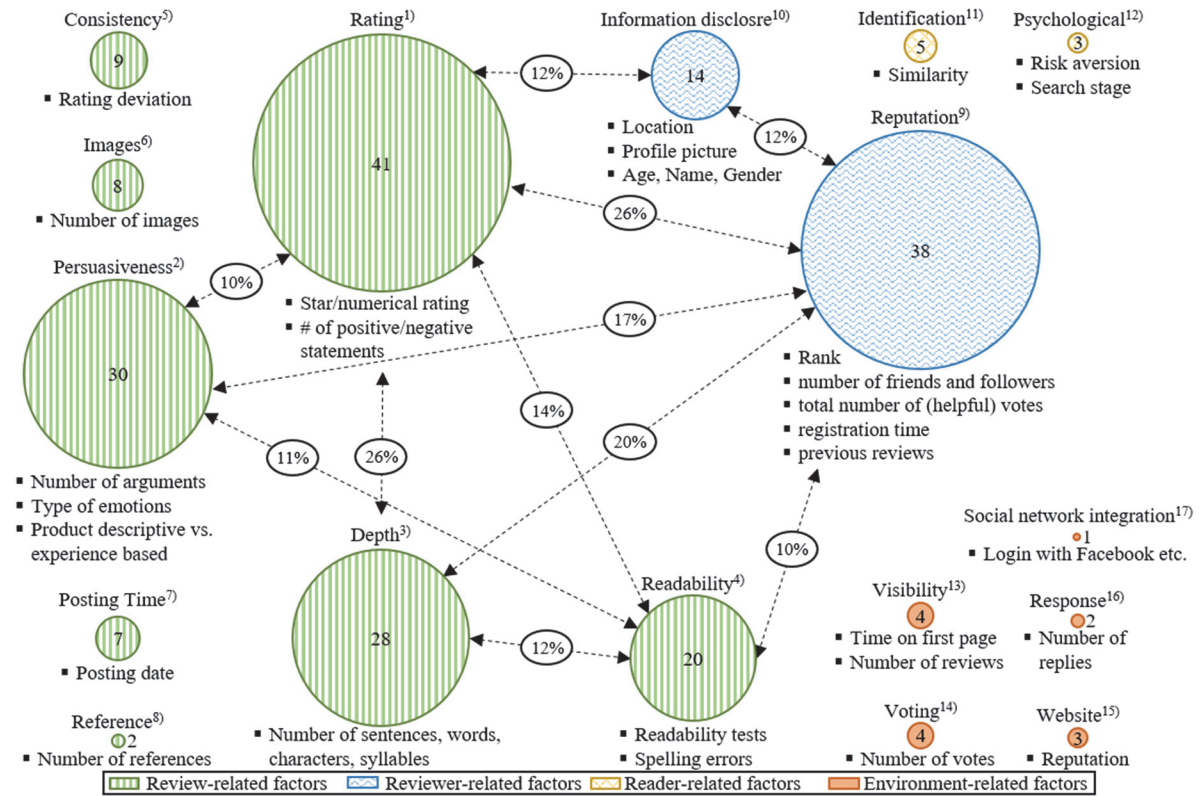
4.1 Criteria determining the helpfulness of online reviews

Figure 2 shows the results of the literature review using co-topic analysis, whereby in our case a topic is a factor. The colored clusters show the different factors in each dimension: review-related, reviewer-related, reader-related and environment-related. The bubble-size represents the relative number of journal articles investigating a factor. Below the bubble, the bullet points show the most important characteristics of this factor. The superscript number at the factor name shows, which article researched this factor. The lines between the bubbles indicate the top ten frequent links of how many times the two factors were researched together.

Regarding the total number of journal articles published per year, the importance of the individual factors remained constant over the years. The size of the bubbles in Figure 2 below indicates how many journal articles investigated each factor, which makes them comparable and shows the current research state. Among the most important factors (at least 10 journal articles), some were found to be more likely to be investigated together. 26% of all journal articles investigated both, the influence of review depth on helpfulness and the effect of review ratings. Other noteworthy interdependencies were found between reputation and rating (26% of all journal articles investigated both factors), depth and reputation (20%), readability and rating (14%), information disclosure and reputation (12%), information disclosure and rating (12%) and readability and depth (12%).

4.2 Review-related factors

Rating. Rating is - next to reviewer reputation - the most important factor for determining the helpfulness of a review (Yang *et al.*, 2017b). Most researchers found that negative reviews are more helpful than positive reviews (Cao *et al.*, 2011; Baek *et al.*, 2013; Zhou and Guo, 2017; Yang *et al.*, 2017a; Zhao *et al.*, 2015; Lee *et al.*, 2011; Li *et al.*, 2017; Casaló *et al.*, 2015; Chua and Banerjee, 2016; Lee, 2013; Lee, 2018; Kwok and Xie, 2016; Yin *et al.*, 2013; Kuan *et al.*, 2015). One possible explanation for this effect is the negativity bias as explained in the theoretical background section. However, if a review is negative and at the same time promotes another product, the review is perceived to be untrustworthy and not helpful at all (Filieri, 2016). Filieri (2016) argues that negative reviews tend to stand-out and are supposedly written by competitors. Few researchers however found that positive reviews are more helpful than negative reviews (Liu and Park, 2015; Huang *et al.*, 2015; Casaló *et al.*, 2015; Pan and Zhang, 2011). Pan and Zhang (2011) explain this finding with the confirmatory bias.



¹ Baek et al. (2013); Baek et al. (2015); Cao et al. (2011); Casaló et al. (2015); Chen (2016); Cheung et al. (2012); Filieri (2016); Gao et al. (2017); Huang et al. (2015); Jensen et al. (2013); Krishnamoorthy (2015); Kuan et al. (2015); Kusumasondjaja et al. (2012); Kwok and Xie (2016); Lee (2013); Lee (2018); Lee and Choeh (2017); Lee and Choeh (2018); Lee et al. (2011); Li et al. (2017); Liu and Park (2015); Mudambi and Schuff (2010); Pan and Zhang (2011); Park and Nicolau (2015); Pentina et al. (2018); Purnawirawan et al. (2012); Quaschnig et al. (2015); Racherla and Friske (2012); Salehan and Kim (2016); Schindler and Bickart (2012); Schlosser (2011); Singh et al. (2017); Weathers et al. (2015); Willemsen et al. (2011); Wu (2013); Yang et al. (2017a); Yang et al. (2017b); Yin et al. (2013); Yin et al. (2016); Zhao et al. (2015); Zhou and Guo (2017)

² Agnihotri and Bhattacharya (2016); Baek et al. (2013); Banerjee and Chua (2014); Chen and Tseng (2011); Cheung et al. (2012); Chong Alain et al. (2018); Chua and Banerjee (2016); Fang et al. (2016); Ghose and Ipeiritos (2011); González-Rodríguez et al. (2016); Huang et al. (2013); Hong et al. (2016); Kim et al. (2017); Krishnamoorthy (2015); Li et al. (2013); Luan et al. (2016); Luo et al. (2015); Malik and Hussain (2017); Racherla et al. (2012); Robinson et al. (2016); Salehan and Kim (2016); Schindler and Bickart (2012); Shan (2016); Shen et al. (2016); Teng et al. (2014); Weathers et al. (2015); Willemsen et al. (2011); Yin et al. (2013); Zhao et al. (2015); Zheng et al. (2013)

³ Baek et al. (2013); Banerjee and Chua (2014); Cheng and Ho (2015); Chua and Banerjee (2014); Filieri (2016); González-Rodríguez et al. (2016); Huang et al. (2015); Korfatis et al. (2012); Kuan et al. (2015); Kwok and Xie (2016); Lee (2018); Lee and Choeh (2017); Lee and Choeh (2018); Liu and Park (2015); Mudambi and Schuff (2010); Pan and Zhang (2011); Park and Nicolau (2015); Qazi et al. (2016); Quaschnig et al. (2015); Racherla and Friske (2012); Robinson et al. (2016); Schindler and Bickart (2012); Singh et al. (2017); Yang et al. (2017a); Yang et al. (2017b); Yin et al. (2013); Yin et al. (2016); Zhou and Guo (2017)

⁴ Agnihotri and Bhattacharya (2016); Banerjee and Chua (2014); Cao et al. (2011); Fang et al. (2016); Filieri (2016); Gao et al. (2017); Ghose and Ipeiritos (2011); Jensen et al. (2013); Korfatis et al. (2012); Kuan et al. (2015); Lee and Choeh (2014); Liu and Park (2015); Ngo-Ye and Sinha (2014); Robinson et al. (2016); Schindler and Bickart (2012); Singh et al. (2017); Yang et al. (2017a); Yin et al. (2013); Zhao et al. (2015); Zheng et al. (2013)

⁵ Baek et al. (2013); Baek et al. (2015); Cheung et al. (2012); Gao et al. (2017); Hong et al. (2016); Luo et al. (2015); Pan and Zhang (2011); Quaschnig et al. (2015); Yin et al. (2016)

⁶ Casaló et al. (2015); Cheng and Ho (2015); Filieri (2016); Lee (2018); Teng et al. (2014); Yang et al. (2017a); Yang et al. (2017b); Zhou and Guo (2017)

⁷ Cao et al. (2011); Hu and Chen (2016); Kuan et al. (2015); Lee (2013); Yin et al. (2016); Zhao et al. (2015); Zhou and Guo (2017)

⁸ Robinson et al. (2016); Weathers et al. (2015)

⁹ Agnihotri and Bhattacharya (2016); Baek et al. (2013); Banerjee et al. (2017); Chen (2016); Cheng and Ho (2015); Cheung et al. (2012); Chong Alain et al. (2018); Chua and Banerjee (2014); Fang et al. (2016); Filieri (2016); González-Rodríguez et al. (2016); Gao et al. (2017); Hu and Chen (2016); Huang et al. (2015); Kim et al. (2017); Kuan et al. (2015); Kwok and Xie (2016); Lee et al. (2011); Lee (2018); Lee and Choeh (2017); Lee and Choeh (2018); Li et al. (2013); Li et al. (2017); Liu and Park (2015); Min and Park (2012); Park and Nicolau (2015); Racherla and Friske (2012); Shan (2016); Shen et al. (2016); Teng et al. (2014); Weathers et al. (2015); Willemsen et al. (2011); Xu (2014); Yang et al. (2017b); Zhao et al. (2015); Zheng et al. (2013); Zhou and Guo (2017); Zhu et al. (2014)

¹⁰ Baek et al. (2013); Gao et al. (2017); Ghose and Ipeiritos (2011); Hong et al. (2016); Kusumasondjaja et al. (2012); Kwok and Xie (2016); Lee and Choeh (2017); Lee et al. (2011); Liu and Park (2015); Otterbacher (2013); Park and Nicolau (2015); Racherla and Friske (2012); Xu (2014); Zhou and Guo (2017)

¹¹ Davis and Agrawal (2017); Guo and Zhou (2017); Pentina et al. (2018); Shan (2016); Teng et al. (2014)

¹² Casaló et al. (2015); Memarzadeh et al. (2016); Robinson et al. (2016)

¹³ Hu and Chen (2016); Kuan et al. (2015); Lee and Choeh (2017); Pan and Zhang (2011)

¹⁴ Lee (2013); Liu and Park (2015); Yang et al. (2017a); Zhao et al. (2015)

¹⁵ Bae and Lee (2011); Chong Alain et al. (2018); Kim et al. (2017)

¹⁶ Kwok and Xie (2016); Ryang et al. (2015)

¹⁷ Huang et al. (2017)

Figure 2: Co-topic analysis of 81 journal articles. Colored clusters: Different dimensions with factors. Bubble-size: Relative number of journal articles investigating a factor. Bullet points: Most important characteristics of this factor. Superscript number: Articles re-researched this factor. Lines: Frequency of how many times the two factors were investigated together (in percent of the total amount of journal articles = 81).

The confirmatory bias describes a situation in which the customers have a pre-decisional preference and if an online review provides validation for this preference, it is perceived to be more helpful (Liu and Park, 2015). However, Pan and Zhang (2011) add that whether positive or negative reviews are more helpful strongly depends on other factors like personality traits and consumption goals and therefore, a generalization of either finding could be dangerous. Regarding product types, Willemsen et al. (2011) concluded that negative reviews are more helpful for experience goods and positive reviews are more helpful for search goods. In contrast, Racherla and Friske (2012) discovered that the negativity effect is only present for search goods and not for experience goods. Some other researchers argue that it depends on the average rating e.g. positive reviews are more helpful for positive average rating (Yin *et al.*, 2016; Quaschnig *et al.*, 2015; Baek *et al.*, 2015). However, Lee (2013) argues that reviews which differ from the average rating deliver more value because they provide new information and therefore, they are more helpful. These findings are strongly contradicting and should therefore be further investigated. Together with rating, many researchers investigated the effect of one- and two-sidedness on the review helpfulness. One-sided reviews contain either positive or negative statements whereas two-sided reviews include positive and negative statements (Cheung *et al.*, 2012). Most researchers agree that two-sided reviews are more helpful compared to one-sided reviews (Cheung *et al.*, 2012; Salehan and Kim, 2016; Willemsen *et al.*, 2011; Schlosser, 2011; Weathers *et al.*, 2015; Jensen *et al.*, 2013; Filieri, 2016; Schindler and Bickart, 2012). Salehan and Kim (2016) argue that one-sided reviews are perceived to be biased. Schlosser (2011) adds that – with the exception of reviews with extreme ratings – two-sided reviews increase the trustworthiness. However, Purnawirawan et al. (2012), Lee and Choeh (2018) and Pentina et al. (2018) also found that one-sided reviews are more helpful. Purnawirawan et al. (2012) argue that one-sided reviews provide a clear direction and therefore increase the perception that the information in the review is true. Furthermore, Lee and Choeh (2018) add that two-sided reviews in general fail to offer a clear statement leaving the reader with uncertainty. The explanation of Pentina et al. (2018) is directed to the confirmation bias. Pentina et al. (2018) argue that users of digital review sites are not looking for objective unbiased information but rather want to confirm their pre-existing intentions. Third and in connection to extremity, Kuan et al. (2015) found that reviews with extreme ratings receive more voting but are perceived to be less helpful. They say that on the one hand moderate rated reviews are more likely to be disregarded and therefore, extreme reviews get more voting but on the other hand extreme rated reviews have a greater potential of being biased (Kuan *et al.*, 2015). Kuan et al. (2015) conclude, that a rating in between the average and the absolute extreme provides the greatest value. Although Mudambi and Schuff (2010) agree with Kuan et al., some other researchers found that extreme ratings increase the review helpfulness (Gao *et al.*, 2017; Yin *et al.*, 2013; Lee and Choeh, 2014; Wu, 2013). In numbers, reviews with either 1- or 5-stars are the most helpful, 2-star reviews are second most helpful and 4- and 3-star reviews are least helpful (Park and Nicolau, 2015). In contrast, Filieri (2016) argues that reviews with extreme ratings were found to be potentially manipulated and therefore rating extremity should always be measured together with other factors which allow the reader to determine whether a review is fake or real.

Persuasiveness. Persuasiveness is determined by the number and strength of the arguments, comprehensiveness, timeliness and sidedness (Chong *et al.*, 2018). Most researchers agree that argument quality increases the helpfulness of a review (Cheung *et al.*, 2012; Shan, 2016; Zhao *et al.*, 2015; Shen *et al.*, 2016). Shan (2016) sees the reason thereof in the greater trustworthiness that is delivered by strong arguments. Zhao et al. (2015) argue that in the anonymity of the internet, people seek for more cues to judge information and that strong arguments make this process of judgment easier. Shen et al. (2016) conclude that readers are more likely to adopt the information of a review if the argument quality is high. Furthermore, the effect of argument quality is stronger if either the reader perceives a strong sense of membership (Luo *et al.*, 2015) or if the similarity of reader and reviewer is high (Racherla *et al.*, 2012). In general, argument quality was found to be one of the strongest determinants of online review helpfulness (Teng *et al.*, 2014; Cheung *et al.*, 2012).

According to Willemsen et al. (2011) a higher number of arguments increases the review helpfulness independently of the argument quality. This is in line with Robinson et al. (2012) who say that information in the review is a strong predictor of its helpfulness.

Emotions also influence the persuasiveness and therefore review helpfulness. However, researchers do not agree on how they affect the review helpfulness (Hong *et al.*, 2016; Salehan and Kim, 2016; Fang *et al.*, 2016; Agnihotri and Bhattacharya, 2016; González-Rodríguez *et al.*, 2016). Ahmad and Laroche (2015) found in their analysis of emotion features that happiness and disgust in a review positively influence helpfulness and that anxiety has a negative effect on helpfulness. However, Yin *et al.* (2013) proclaim that reviews containing anxiety are more helpful than reviews containing anger. Although these findings are contradictory, two interesting observations were made by Malik and Hussain and by Banerjee and Chua. First, Malik and Hussain (2017) stated that positive emotion features (e.g. trust, anticipation and joy) are better predictors of helpfulness than negative emotion features (e.g. anxiety, sadness and anger). Second, Banerjee and Chua (2014) found fewer negative emotion words in negative reviews that were voted as helpful and fewer positive emotion words in positive reviews that were voted as helpful.

Regarding persuasiveness connected to product types, most researchers agree that reviews with more product descriptive statements are more helpful for search goods (Luan *et al.*, 2016; Chua and Banerjee, 2016; Malik and Hussain, 2017; Huang *et al.*, 2013; Krishnamoorthy, 2015; Weathers *et al.*, 2015). Some argue that product descriptive statements in general increase the helpfulness (Schindler and Bickart, 2012; Zheng *et al.*, 2013; Chen and Tseng, 2011). Weathers *et al.* (2015) add that information about the usage of the product increases the helpfulness for both product types. However, experience-based reviews seem to be more helpful for experience goods (Malik and Hussain, 2017; Huang *et al.*, 2013; Krishnamoorthy, 2015). Luan *et al.* (2016) found that for experience goods in general it does not matter whether a review is attribute- or experience-based because the reader simply wants to get as much information as possible. This statement is in accordance with Zheng *et al.* (2013) and Chen and Tseng (2011) respectively who say that personal experience and opinions increase the helpfulness.

Persuasiveness is further linked to subjectivity/objectivity. In general, it is easier to determine the helpfulness of objective reviews (Zheng *et al.*, 2013). Therefore, objective reviews are often considered to be more helpful (Kim *et al.*, 2017; Li *et al.*, 2013). Nevertheless, a mixture of objective sentences mixed with extreme subjective content was also found to be helpful (Ghose and Ipeirotis, 2011).

Depth. Regarding review depth, most researchers found that longer reviews are more helpful (Cheng and Ho, 2015; Yin *et al.*, 2016; Zhou and Guo, 2017; Park and Nicolau, 2015; Yin *et al.*, 2013; González-Rodríguez *et al.*, 2016; Liu and Park, 2015; Quaschnig *et al.*, 2015; Lee and Choeh, 2017; Yang *et al.*, 2017a; Lee, 2018). However, reviews can also be too long and therefore, review helpfulness increases proportional to length but only up to a certain point (Baek *et al.*, 2013; Schindler and Bickart, 2012). One simple explanation for this finding is that longer reviews have a higher chance of providing more information to the reader. Nevertheless, at the same time, in the case of long average reviews, an even longer review fails to attract the readers' attention, because the reader must put in more effort into reading the longer review for a perceived small amount of extra information (Qazi *et al.*, 2016; Chua and Banerjee, 2014). For DVDs, e.g., reviews with more than 430 words were found to be too long, for books a review should contain around 230 words to be exceptionally helpful (Kuan *et al.*, 2015).

Findings regarding length in connection with product type show that length is more important for search goods than experience goods but it is an important factor for both product types (Baek *et al.*, 2013; Mudambi and Schuff, 2010; Pan and Zhang, 2011). In contrast, Racherla and Friske (2012) found that longer reviews for experience goods can be less helpful. A possible explanation therefore is that due to the many available reviews and the connected information overload, consumers are overwhelmed and do not pay attention to longer reviews (Racherla and Friske, 2012). Additionally, the positive effect of review length is weaker for negative reviews (Banerjee and Chua, 2014) and among top reviewers, the effect of review length is insignificant (Huang *et al.*, 2015). Length compared to other factors only has a small impact on helpfulness (Singh *et al.*, 2017). Factors like readability, rating or reputation of the reviewer are more important (Korfiatis *et al.*, 2012; Yang *et al.*, 2017b). An explanation for this is provided by Robinson *et al.* (2012) who say that length preferences strongly depend on the search stage of the recipient. E.g. in an early search stage, the reader tries to get an overview of the product and prefers shorter reviews, however, in a late search stage, the reader prefers longer reviews to collect detailed information about the product.

In contrast to most other researchers, Kwok and Xie (2016) found shorter reviews to be more helpful which they affiliated with greater readability and Qazi et al. (2016) discovered that shorter reviews are more helpful if they are suggestive. However, Filieri (2016) disagrees because his research revealed that short reviews are perceived to be fake and untrustworthy. Filieri (2016) argues that short reviews often do not provide detailed information about product or usage experiences. Especially in connection with sensational titles, emotional and gushy language and the use of superlatives shorter reviews are frequently perceived to be fake (Filieri, 2016).

Readability. Regarding readability, Singh et al. (2017) found that it is a strong indicator of review helpfulness for both, search and experience goods. However, researchers found mixed findings for the direction of the effect. Some researchers concluded that less readable reviews with longer sentences and more complex words are more helpful, because they are considered as more professional (Kuan *et al.*, 2015; Yang *et al.*, 2017a). Agnihotri and Bhattacharya (2016) agree that too simplistic reviews are less helpful but nevertheless found that readability increases the review helpfulness although only up to a certain point. Most researchers, however, represent the opinion that greater readability in general increases review helpfulness (Zhao *et al.*, 2015; Banerjee and Chua, 2014; Ghose and Ipeirotis, 2011; Fang *et al.*, 2016; Liu and Park, 2015; Yin *et al.*, 2013). According to Ghose and Ipeirotis (2011) readability improves the comprehensibility of reviews and therefore a larger number of users can potentially read it and give voting.

Korfiatis et al. (2012) compared the effect strength of different factors and found that readability has a greater impact on helpfulness than review length. Regarding language in general, promotional language decreases the helpfulness because customer do not trust these kind of reviews (Filieri, 2016). However, humor and slang can increase the helpfulness but only up to a certain point (Schindler and Bickart, 2012). Schindler and Bickart (2012) argue that the informal style can increase the readers feeling of similarity with the reviewer and therefore makes the review more helpful. However, too much informality can make the reader feel uncertain regarding the reviewers competence (Schindler and Bickart, 2012). According to Robinson et al. (2012) and Singh et al. (2017), spelling mistakes only have a minor impact on helpfulness. Nevertheless, various researchers found that few spelling mistakes and short sentences with familiar words increase the helpfulness of a review (Zheng *et al.*, 2013; Ghose and Ipeirotis, 2011; Cao *et al.*, 2011; Lee and Choeh, 2014). Summarized, language influences the perception of reviews in different ways and therefore, text mining methods can be useful for the prediction of review helpfulness (Ngo-Ye and Sinha, 2014).

Consistency. Most researchers found that consistency with previous reviews increases the helpfulness of a review (Baek *et al.*, 2013; Baek *et al.*, 2015; Luo *et al.*, 2015; Yin *et al.*, 2016; Cheung *et al.*, 2012; Quaschnig *et al.*, 2015). However, Baek et al. (2013) found that this factor is more important for experience goods and for products with a low price. They argue that it depends on the purpose of reading online reviews and that in the case of experience goods and low-priced products most people are narrowing down possible choice options rather than evaluating alternatives (Baek *et al.*, 2013). Strong disagreement among reviews leads to a decrease in the helpfulness of all reviews because of the resulting uncertainty for the reader (Pan and Zhang, 2011). However, some researchers found reviews with a strong deviation from the average rating to be more helpful for the reader (Hong *et al.*, 2016; Gao *et al.*, 2017). This might be explained by the greater amount of information delivered by an inconsistent review. The explanation is similar to the argumentation of the negativity bias, which concludes that negative reviews are more helpful than positive reviews because of providing newer information.

Images. Occasionally, reviewers add images to their reviews. Filieri (2016) regards images as proof that the reviewers used the reviewed product and therefore he argues, that images increase the helpfulness. Other researchers support this finding (Cheng and Ho, 2015; Zhou and Guo, 2017; Teng *et al.*, 2014). Additionally, Yang et al. (2017a) discovered that images of the food and beverages increase the helpfulness of restaurant reviews. However, Lee (2018) and Casalo et al. (2015) disagree because they found that images have an insignificant effect on the review helpfulness.

Posting time. Posting time directly influences review helpfulness because more recently posted reviews get more helpfulness votes (Zhou and Guo, 2017; Zhao *et al.*, 2015; Cao *et al.*, 2011; Yin *et al.*, 2016).

Lee (2013) found the exact opposite, namely that early posted reviews are read more often and therefore receive more voting (Kuan *et al.*, 2015). It is possible that the most helpful review of a product is the most helpful review among early posted reviews only (Lee, 2013). Therefore, posting time is generally important for the prediction of review helpfulness (Hu and Chen, 2016).

References. Either references in reviews can be directed to other reviews or they are used to compare the product to products from other brands. Weathers *et al.* (2015) found that references to other brands significantly increase the helpfulness for experience goods but have almost no effect for search goods. References to other reviews increase helpfulness for both product types (Weathers *et al.*, 2015). According to Robinson *et al.* (2012) references increase the amount of information in a review and therefore generally rise its helpfulness.

4.3 Reviewer-related factors

Reputation. Reputation has a strong impact on review helpfulness (Chua and Banerjee, 2016). High ranked, credible reviewers write more helpful reviews (Kuan *et al.*, 2015; Lee and Choeh, 2018; Cheng and Ho, 2015; Kwok and Xie, 2016; Zhu *et al.*, 2014; Park and Nicolau, 2015; Li *et al.*, 2017; Banerjee *et al.*, 2017; Racherla and Friske, 2012; Cheung *et al.*, 2012; Shen *et al.*, 2016; Teng *et al.*, 2014; Chong *et al.*, 2018; Baek *et al.*, 2013). This factor is more important for experience goods and products with a lower price (Baek *et al.*, 2013; Zhu *et al.*, 2014). E.g. for higher priced hotels, the effect of credibility was found to be weaker than for lower priced hotels (Zhu *et al.*, 2014). Zhu *et al.* (2014) argue that the cognitive trust is stronger for lower priced hotels. However, other sub-factors of reputation like the review rating and the total number of helpfulness votes a reviewer received in the past have a greater effect on review helpfulness (Shan, 2016).

The helpfulness of future reviews is greatly determined by the reviewers' capability of writing helpful reviews (Lee and Choeh, 2018). Gao *et al.* (2017) found that the rating behavior of reviewers is consistent over time and that therefore reviewers who write helpful reviews in the past are more likely to write helpful reviews in the future (Fang *et al.*, 2016; Banerjee *et al.*, 2017). In general, the total number of helpfulness votes or the average helpfulness of a reviewer (total number of helpfulness votes / total number of votes) is a good predictor of the helpfulness of future reviews (Lee and Choeh, 2017; Huang *et al.*, 2015; Banerjee *et al.*, 2017; Yang *et al.*, 2017b; Zheng *et al.*, 2013; Kwok and Xie, 2016). Therefore, most researchers agree that expertise - based on credentials of others (e.g. votes) - of the reviewer increases the helpfulness of his/her reviews (Agnihotri and Bhattacharya, 2016; Zhu *et al.*, 2014; Zhou and Guo, 2017; Willemsen *et al.*, 2011; Park and Nicolau, 2015; Kim *et al.*, 2017; Lee *et al.*, 2011; González-Rodríguez *et al.*, 2016; Zhao *et al.*, 2015; Weathers *et al.*, 2015). However, Min and Park (2012) disagree and warn of a possible early bird bias. They found that the number of experiences mentioned in the review is much more important.

Various researchers discovered that the total number of reviews written by a reviewer increases the trustworthiness and makes future reviews more helpful (Banerjee *et al.*, 2017; Filieri, 2016; Lee *et al.*, 2011; Lee, 2018). However, Huang *et al.* (2015) argue that this is not a significant factor because quantity does not correlate with quality.

Sociability or the total number of friends and followers of a reviewer can be used as an indicator of helpfulness of his/her reviews (Cheng and Ho, 2015; Liu and Park, 2015; Lee, 2018; Zheng *et al.*, 2013; Banerjee *et al.*, 2017; Zhou and Guo, 2017; Li *et al.*, 2017). Cheng and Ho (2015) argue that the number of followers is an indicator that the reviewer is an opinion leader and that he is trusted by many other readers. Liu and Park (2015) add that social information can be used to assess the source of a review and to judge the credibility of a reviewer. This has an effect on the uncertainty reduction regarding the service quality (Liu and Park, 2015). However, Xu (2014) differentiated between positive and negative reviews and found that sociability only increases the perceived helpfulness of negative reviews.

Information disclosure. Information disclosure leads to more helpfulness votes (Ghose and Ipeiritis, 2011; Kusumasondjaja *et al.*, 2012). Gao *et al.* (2017) found that intrinsic characteristics (e.g. culture, gender) capture the largest fraction of future rating deviation. The location of a reviewer can give a hint on the cultural background, which allows conclusions about the degree of conformity of his/her reviews

with other reviews. Hong et al. (2016) discovered that on one hand, reviewer from a collectivist culture are less likely to deviate from the average rating and that they express less emotions. However, reviewers from an individualistic culture are more likely to deviate from the prior rating and they express more emotions (Hong *et al.*, 2016). The disclosure of the real name of the reviewer increases his/her credibility and the helpfulness of the reviews (Lee and Choeh, 2017). Various researchers found that the disclosure of a profile picture increases the review helpfulness (Zhou and Guo, 2017; Liu and Park, 2015; Park and Nicolau, 2015). Xu (2014) observed the same effect but only for negative reviews. Regarding the gender, Kwok and Xie (2016) found that reviews written by male reviewers are more helpful than reviews written by female reviewers (reviews written by female reviewers are 13.6% less helpful). A reason for this could be that reviews written by male reviewers have the tendency to be more fact based (Kwok and Xie, 2016). Additionally, Otterbacher (2013) investigated the differences in male and female writing and found that helpful reviews written by female writers often show male style characteristics (e.g. less vocabulary richness, decreased use of 1st and 2nd person pronouns). In contrast to these findings, Lee et al. (2011) revealed that men and women create similarly helpful reviews and that not disclosing the gender increases the helpfulness. Lee et al. (2011) argue that people who do not disclose their gender probably use the anonymity to share their experiences and personal feelings more openly and therefore the reader perceives these reviews to be more honest and sincere. Finally, the age of the reviewer has no influence on review helpfulness (Kwok and Xie, 2016; Lee *et al.*, 2011).

4.4 Reader-related factors

Similarity. Perceived similarity between the reader and the reviewer influences the information adoption (Davis and Agrawal, 2018). The greater the similarity, the higher is the helpfulness of a review (Pentina *et al.*, 2018; Shan, 2016; Teng *et al.*, 2014). The helpfulness of positive reviews is increased, when the reviewer uses the same linguistic style as the reader would use (Guo and Zhou, 2017). If the reader perceives the reviewer to be on an equal level of expertise as himself, negative reviews are more helpful (Guo and Zhou, 2017).

Psychology. Psychological factors can influence the way a reader perceives a review. First, the extent to which the reader believes that a certain review can change his/her behavior positively influences the review helpfulness (Memarzadeh *et al.*, 2016). Second, the risk aversion of the reader changes the readers' preference regarding positive and negative reviews. High risk aversion readers prefer negative reviews, low risk aversion readers have no preference for either positive or negative reviews (Casaló *et al.*, 2015). Third, the search stage has a great influence on the effect of the factor depth (Robinson *et al.*, 2012). Reader in an early search stage prefer shorter reviews because they try to get a general overview on different products and later on, they prefer longer reviews to get detailed information about specific products (Robinson *et al.*, 2012).

4.5 Environment-related factors

Visibility. The total number of reviews available for a product has a significant impact on the review helpfulness (Lee and Choeh, 2017). This has to do with the visibility of the reviews, if there are fewer reviews, each review has the potential to offer new information and therefore, the helpfulness of each single review increases (Pan and Zhang, 2011). In general, when conducting research about review helpfulness, it is very important to include the visibility factor because the total number of reviews is negatively correlated with voting and therefore can distort the results (Hu and Chen, 2016; Kuan *et al.*, 2015).

Voting systems. Voting systems generally increase the helpfulness of review websites because they allow the reader to quickly assess whether a review should be/should not be considered in the purchase decision (Zhao *et al.*, 2015). Thereby, not only voting systems for helpfulness are relevant, but also voting systems for enjoyment (Liu and Park, 2015). Enjoyment of a review is positively related to the helpfulness of the review (Yang *et al.*, 2017a). Liu and Park (2015) argue that in the computer-mediated environment, individuals are seeking entertainment and therefore enjoyable reviews are more helpful.

The effect of voting is greater for search goods than for experience goods because people who are looking for reviews about search goods are more interested in opinions of others (Lee, 2013).

Review website. Various review websites (e.g. Yelp, TripAdvisor) can be found online. Readers assign them with different credibility levels depending on their awareness level. Kim et al. (2017) found that the website credibility influences the helpfulness of a review. So does the perceived ease of use of the website (Chong *et al.*, 2018). Regarding the provider of the website, reviews about experience products are more helpful if posted on a consumer developed review site (Bae and Lee, 2011). In contrast to review websites, consumer developed review sites are defined as online communities or blogs (Bae and Lee, 2011). Bae and Lee (2011) argue that customers who want to evaluate the dominant attributes of experience goods expect to benefit more from these kind of websites.

Responses. The helpfulness of a review is increased whenever the management of the rated service or product responds to the review (Kwok and Xie, 2016). Kwok and Xie (2016) argue that reviews with a response of the management often include detailed information and provide more reference value to the readers. Furthermore, the manager response is regarded as a cross-validation of the information in the review (Kwok and Xie, 2016). Additionally, discussions between users also increase the review helpfulness, especially when the reviewer himself is actively involved in the discussion (Ryang *et al.*, 2015). Ryang et al. (2015) argue that the discussion provides the opportunity to further elaborate on the shared opinions.

Social network integration. Social network integration was found to increase the review volume. At the same time, less negations were used in the reviews while more positive emotions were expressed (Huang *et al.*, 2017).

5 Discussion

5.1 Implications

The previous research primarily focused on factors related to the reviews itself and to the reviewer who wrote the reviews. Reader-related factors and environment-related factors got less attention in general. Additionally, within the four dimensions, some factors were analyzed by significantly more researchers than other factors. Regarding the individual factors, sometimes it is possible to make a clear statement whether the factors increases or decreases the helpfulness while for others it is very hard to tell because of mixed findings.

The most important findings are summarized subsequently. Extremely rated reviews are of great value for the readers while negative reviews are more helpful than positive ones. Nevertheless, the combination of positive and negative statements increases the review helpfulness. A higher number of arguments as well as the argument quality positively affects the helpfulness of a review. Regarding emotions, the findings were mixed and need further research. Reviews with many product descriptive statements are more helpful for reviews about search goods while experience-based reviews are more helpful for reviews about experience goods. Longer reviews provide greater value to the reader than short reviews, but only up to a certain point. Readability, consistency with previous reviews and references to other brands and reviews increase the review helpfulness. Posting time and the inclusion of images seem to be important factors but their effect is not yet fully discovered. Regarding the reviewer, online reputation and information disclosure both increase the helpfulness of his/her reviews. The similarity between the reader and the reviewer has a positive effect on review helpfulness. Finally, the website credibility and replies to the review both make a review more helpful to the reader. To get new perspectives, further researchers should consider doing a qualitative research instead of quantitative. Finally, all the theoretical knowledge should be condensed into a model or program and then be tested.

5.2 Limitations and Future Research

One limitation of this literature review is the selection process of the journal articles, the scope and the extraction of information. For every step, strict rules were predefined. Additionally, all steps were precisely documented. However, all decisions that were made when setting the rules have an influence on the outcome of the literature review. First, the limitation that journal articles published between 2011 to mid-2018 were included automatically excluded some journal articles. Second, journal articles, which were not published in a top journal, were excluded. Additionally, the chosen databases have an impact on the origin of the journal articles. This also explains why most journal articles that were used in the final analysis are from the research field of information systems. We used the new invented visualization method called co-topic analysis in our literature review. Further research needs to be carried out showing the generalizability of the used method. Our next step includes training a machine-learning algorithm for automatically extracting topics from research paper and creating the visualization.

Future research regarding the helpfulness of online reviews should focus on reader-related factors and environment-related factors because the co-topic analysis showed that these two dimensions got less attention in the previous research. E.g. a topic that was greatly disregarded so far is the influence of social media. In the digital age, sharing of information through social media is of great importance (Aggarwal, 2016). People share their opinions in these likeminded communities and it is hard to separate fake from real. Therefore, researchers should investigate factors, which are related to digital sharing in social networks and find ways to predict the helpfulness of reviews that are shared on social media. Additionally, more in-depth knowledge regarding the effects of review-related factors would be helpful to solve the problem of mixed findings. To complete the ‘big picture’, the research needs more connections between the individual factors in general.

6 Conclusion

The presented systematic literature review investigated the characteristics determining the helpfulness of online reviews. The results are based on 81 journal articles, which we analyzed in depth. This paper contributes to both theory and practice alike. We contribute to theory, by inductively creating a theoretical framework trying to understand the context of online reviews and their characteristics. Furthermore, through the application of 1) review-related, 2) reviewer-related, 3) reader-related and 4) environment-related factors, we offer a conceptualization of what contributes to the perceived helpfulness of an online review. Most literature concentrates on the factors in dimension one and two. This provides the opportunity for further research regarding the factors in dimension three and four. Additionally, many researchers focused on different factors individually and neglected investigating the connection between them. Therefore, the linkage between the factors can be seen as area for future research. We contribute to practice by providing insights in how to design a review system, guiding reviewers to write helpful reviews and new ways of how to display the most helpful reviews. Additionally our contribution is a new visualization approach we call co-topic analysis. This helps researches to identify links between topics and showing an in depth overview, of which topics were researched by whom.

7 References

- Aggarwal, A. (2016), “A Hybrid Approach to Big Data Systems Development”, in *Managing Big Data integration in the public sector*, IGI Global, pp. 20–37.
- Agnihotri, A. and Bhattacharya, S. (2016), “Online review helpfulness: Role of qualitative factors”, *Psychology & Marketing*, Vol. 33 No. 11, pp. 1006–1017.
- Ahmad, S.N. and Laroche, M. (2015), “How do expressed emotions affect the helpfulness of a product review? Evidence from reviews using latent semantic analysis”, *International Journal of Electronic Commerce*, Vol. 20 No. 1, pp. 76–111.
- Ba, S. and Pavlou, P.A. (2002), “Evidence of the effect of trust building technology in electronic markets: Price premiums and buyer behavior”, *MIS quarterly*, Vol. 26 No. 3, pp. 243–268.

- Bae, S. and Lee, T. (2011), "Product type and consumers' perception of online consumer reviews", *Electronic Markets*, Vol. 21 No. 4, pp. 255–266.
- Baek, H., Ahn, J.H. and Choi, Y. (2013), "Helpfulness of online consumer reviews: Readers' objectives and review cues", *International Journal of Electronic Commerce*, Vol. 17 No. 2, pp. 99–126.
- Baek, H., Lee, S., Oh, S. and Ahn, J. (2015), "Normative social influence and online review helpfulness: Polynomial modeling and response surface analysis", *Journal of Electronic Commerce Research*, Vol. 16 No. 4, pp. 290–306.
- Banerjee, S., Bhattacharyya, S. and Bose, I. (2017), "Whose online reviews to trust? Understanding reviewer trustworthiness and its impact on business", *Decision Support Systems*, Vol. 96, pp. 17–26.
- Banerjee, S. and Chua, A. (2014), "A theoretical framework to identify authentic online reviews", *Online Information Review*, Vol. 38 No. 5, pp. 634–649.
- Cao, Q., Duan, W. and Gan, Q. (2011), "Exploring determinants of voting for the "helpfulness" of online user reviews: A text mining approach", *Decision Support Systems*, Vol. 50 No. 2, pp. 511–521.
- Casaló, L.V., Flavián, C., Guinalíu, M. and Ekinci, Y. (2015), "Avoiding the dark side of positive online consumer reviews: Enhancing reviews' usefulness for high risk-averse travelers", *Journal of Business Research*, Vol. 68 No. 9, pp. 1829–1835.
- Chen, C.C. and Tseng, Y.-D. (2011), "Quality evaluation of product reviews using an information quality framework", *Decision Support Systems*, Vol. 50 No. 4, pp. 755–768.
- Chen, P.-Y., Wu, S.-y. and Yoon, J. (2004), "The impact of online recommendations and consumer feedback on sales", *ICIS 2004 Proceedings*, Vol. 58.
- Chen, Y. and Xie, J. (2008), "Online consumer review: Word-of-mouth as a new element of marketing communication mix", *Management Science*, Vol. 54 No. 3, pp. 477–491.
- Cheng, Y.-H. and Ho, H.-Y. (2015), "Social influence's impact on reader perceptions of online reviews", *Journal of Business Research*, Vol. 68 No. 4, pp. 883–887.
- Cheung, C.M.-Y., Sia, C.-L. and Kuan, K.K.Y. (2012), "Is this review believable? A study of factors affecting the credibility of online consumer reviews from an ELM perspective", *Journal of the Association for Information Systems*, Vol. 13 No. 8, pp. 618–635.
- Chong, A.Y.L., Khong, K.W., Ma, T., McCabe, S. and Wang, Y. (2018), "Analyzing key influences of tourists' acceptance of online reviews in travel decisions", *Internet Research*, Vol. 28 No. 3, pp. 564–586.
- Chua, A.Y.K. and Banerjee, S. (2014), "Understanding review helpfulness as a function of reviewer reputation, review rating, and review depth", *Journal of the Association for Information Science and Technology*, Vol. 66 No. 2, pp. 354–362.
- Chua, A.Y.K. and Banerjee, S. (2016), "Helpfulness of user-generated reviews as a function of review sentiment, product type and information quality", *Computers in Human Behavior*, Vol. 54, pp. 547–554.
- Davis, J.M. and Agrawal, D. (2018), "Understanding the role of interpersonal identification in online review evaluation: An information processing perspective", *International Journal of Information Management*, Vol. 38 No. 1, pp. 140–149.
- Ert, E., Fleischer, A. and Magen, N. (2016), "Trust and reputation in the sharing economy: The role of personal photos in Airbnb", *Tourism Management*, Vol. 55, pp. 62–73.
- Fang, B., Ye, Q., Kucukusta, D. and Law, R. (2016), "Analysis of the perceived value of online tourism reviews: Influence of readability and reviewer characteristics", *Tourism Management*, Vol. 52, pp. 498–506.
- Filieri, R. (2016), "What makes an online consumer review trustworthy?", *Annals of Tourism Research*, Vol. 58, pp. 46–64.
- Fradkin, A., Grewal, E. and Holtz, D. (2018), "The determinants of online review informativeness: Evidence from field experiments on Airbnb", *Ssrn Electronic Journal*.
- Gao, B., Hu, N. and Bose, I. (2017), "Follow the herd or be myself? An analysis of consistency in behavior of reviewers and helpfulness of their reviews", *Decision Support Systems*, Vol. 95, pp. 1–11.

- Ghose, A. and Ipeirotis, P.G. (2011), "Estimating the helpfulness and economic impact of product reviews: Mining text and reviewer characteristics", *IEEE Transactions on Knowledge and Data Engineering*, Vol. 23 No. 10, pp. 1498–1512.
- González-Rodríguez, M.R., Martínez-Torres, R. and Toral, S. (2016), "Post-visit and pre-visit tourist destination image through eWOM sentiment analysis and perceived helpfulness", *International Journal of Contemporary Hospitality Management*, Vol. 28 No. 11, pp. 2609–2627.
- Guo, B. and Zhou, S. (2017), "What makes population perception of review helpfulness: an information processing perspective", *Electronic Commerce Research*, Vol. 17 No. 4, pp. 585–608.
- Hong, Y., Huang, N., Burtch, G. and Li, C. (2016), "Culture, conformity and emotional suppression in online reviews", *Journal of the Association for Information Systems*, Vol. 17 No. 11, pp. 1–38.
- Hu, Y.-H. and Chen, K. (2016), "Predicting hotel review helpfulness: The impact of review visibility, and interaction between hotel stars and review ratings", *International Journal of Information Management*, Vol. 36 No. 6, pp. 929–944.
- Huang, A.H., Chen, K., Yen, D.C. and Tran, T.P. (2015), "A study of factors that contribute to online review helpfulness", *Computers in Human Behavior*, Vol. 48, pp. 17–27.
- Huang, L., Tan, C.-H., Ke, W. and Wei, K.-K. (2013), "Comprehension and assessment of product reviews: A review-product congruity proposition", *Journal of Management Information Systems*, Vol. 30 No. 3, pp. 311–343.
- Huang, N., Hong, Y. and Burtch, G. (2017), "Social network integration and user content generation: Evidence from natural experiments", *MIS quarterly*, Vol. 41 No. 4, pp. 1035–1058.
- Jensen, M.L., Averbeck, J.M., Zhang, Z. and Wright, K.B. (2013), "Credibility of anonymous online product reviews: A language expectancy perspective", *Journal of Management Information Systems*, Vol. 30 No. 1, pp. 293–324.
- Kim, K., Cheong, Y. and Kim, H. (2017), "User-generated product reviews on the internet: the drivers and outcomes of the perceived usefulness of product reviews", *International Journal of Advertising*, Vol. 36 No. 2, pp. 227–245.
- Korfiatis, N., García-Bariocanal, E. and Sánchez-Alonso, S. (2012), "Evaluating content quality and helpfulness of online product reviews: The interplay of review helpfulness vs. review content", *Electronic Commerce Research and Applications*, Vol. 11 No. 3, pp. 205–217.
- Krishnamoorthy, S. (2015), "Linguistic features for review helpfulness prediction", *Expert Systems with Applications*, Vol. 42 No. 7, pp. 3751–3759.
- Kuan, K.K.Y., Hui, K.-L., Prasarnphanich, P. and Lai, H.-Y. (2015), "What makes a review voted? An empirical investigation of review voting in online review systems", *Journal of the Association for Information Systems*, Vol. 16 No. 1, pp. 48–71.
- Kusumasondjaja, S., Shanka, T. and Marchegiani, C. (2012), "Credibility of online reviews and initial trust: The roles of reviewer's identity and review valence", *Journal of Vacation Marketing*, Vol. 18 No. 3, pp. 185–195.
- Kwok, L. and Xie, K.L. (2016), "Factors contributing to the helpfulness of online hotel reviews: Does manager response play a role?", *International Journal of Contemporary Hospitality Management*, Vol. 28 No. 10, pp. 2156–2177.
- Lauterbach, D., Truong, H., Shah, T. and Adamic, L. (2009), "Surfing a web of trust: Reputation and reciprocity on couchsurfing.com", *IEEE 2009 – Computational science and engineering*, Vol. 4, pp. 346–353.
- Lee, H.-A., Law, R. and Murphy, J. (2011), "Helpful reviewers in TripAdvisor, an online travel community", *Journal of Travel & Tourism Marketing*, Vol. 28 No. 7, pp. 675–688.
- Lee, I. (2018), "Usefulness, funniness, and coolness votes of viewers: An analysis of social shoppers' online reviews", *Industrial Management & Data Systems*, Vol. 118 No. 4, pp. 700–713.
- Lee, J. (2013), "What makes people read an online review? The relative effects of posting time and helpfulness on review readership", *Cyberpsychology, Behavior, and Social Networking*, Vol. 16 No. 7, pp. 529–535.
- Lee, S. and Choeh, J.Y. (2014), "Predicting the helpfulness of online reviews using multilayer perceptron neural networks", *Expert Systems with Applications*, Vol. 41 No. 6, pp. 3041–3046.

- Lee, S. and Choeh, J.Y. (2017), "Exploring the determinants of and predicting the helpfulness of online user reviews using decision trees", *Management Decision*, Vol. 55 No. 4, pp. 681–700.
- Lee, S. and Choeh, J.Y. (2018), "The interactive impact of online word-of-mouth and review helpfulness on box office revenue", *Management Decision*, Vol. 56 No. 4, pp. 849–866.
- Li, H., Zhang, Z., Meng, F. and Janakiraman, R. (2017), "Is peer evaluation of consumer online reviews socially embedded?—An examination combining reviewer's social network and social identity", *International Journal of Hospitality Management*, Vol. 67, pp. 143–153.
- Li, M., Huang, L., Tan, C.-H. and Wei, K.-K. (2013), "Helpfulness of online product reviews as seen by consumers: Source and content features", *International Journal of Electronic Commerce*, Vol. 17 No. 4, pp. 101–136.
- Liu, Z. and Park, S. (2015), "What makes a useful online review? Implication for travel product websites", *Tourism Management*, Vol. 47, pp. 140–151.
- Luan, J., Yao, Z., Zhao, F. and Liu, H. (2016), "Search product and experience product online reviews: an eye-tracking study on consumers' review search behavior", *Computers in Human Behavior*, Vol. 65, pp. 420–430.
- Luo, C., Luo, X.R., Xu, Y., Warkentin, M. and Sia, C.L. (2015), "Examining the moderating role of sense of membership in online review evaluations", *Information & Management*, Vol. 52 No. 3, pp. 305–316.
- Malik, M.S.I. and Hussain, A. (2017), "Helpfulness of product reviews as a function of discrete positive and negative emotions", *Computers in Human Behavior*, Vol. 73, pp. 290–302.
- Memarzadeh, F., Blum, S.C. and Adams, C. (2016), "Business Travelers' Intention to Purchase: The Application of Technology Acceptance Model (TAM)", *Journal of Quality Assurance in Hospitality & Tourism*, Vol. 17 No. 4, pp. 412–424.
- Min, H.-J. and Park, J.C. (2012), "Identifying helpful reviews based on customer's mentions about experiences", *Expert Systems with Applications*, Vol. 39 No. 15, pp. 11830–11838.
- Mudambi, S.M. and Schuff, D. (2010), "Research note: What makes a helpful online review? A study of customer reviews on Amazon. com", *MIS quarterly*, Vol. 34 No. 1, pp. 185–200.
- Neat, R. (2015), "Volkswagen under investigation over illegal software that masks emissions", *The Guardian*, 18 September, available at: <https://www.theguardian.com/business/2015/sep/18/epa-california-investigate-volkswagen-clean-air-violations> (accessed 31 October 2018).
- Ngo-Ye, T.L. and Sinha, A.P. (2014), "The influence of reviewer engagement characteristics on online review helpfulness: A text regression model", *Decision Support Systems*, Vol. 61, pp. 47–58.
- Otterbacher, J. (2013), "Gender, writing and ranking in review forums: a case study of the IMDb", *Knowledge and information systems*, Vol. 35 No. 3, pp. 645–664.
- Pan, Y. and Zhang, J.Q. (2011), "Born unequal: a study of the helpfulness of user-generated product reviews", *Journal of retailing*, Vol. 87 No. 4, pp. 598–612.
- Park, S. and Nicolau, J.L. (2015), "Asymmetric effects of online consumer reviews", *Annals of Tourism Research*, Vol. 50, pp. 67–83.
- Pavlou, P.A. and Gefen, D. (2004), "Building effective online marketplaces with institution-based trust", *Information Systems Research*, Vol. 15 No. 1, pp. 37–59.
- Pentina, I., Bailey, A.A. and Zhang, L. (2018), "Exploring effects of source similarity, message valence, and receiver regulatory focus on yelp review persuasiveness and purchase intentions", *Journal of Marketing Communications*, Vol. 24 No. 2, pp. 125–145.
- Purnawirawan, N., Pelsmacker, P. de and Dens, N. (2012), "Balance and sequence in online reviews: How perceived usefulness affects attitudes and intentions", *Journal of interactive marketing*, Vol. 26 No. 4, pp. 244–255.
- Qazi, A., Syed, K.B.S., Raj, R.G., Cambria, E., Tahir, M. and Alghazzawi, D. (2016), "A concept-level approach to the analysis of online review helpfulness", *Computers in Human Behavior*, Vol. 58, pp. 75–81.
- Quaschnig, S., Pandelaere, M. and Vermeir, I. (2015), "When consistency matters: The effect of valence consistency on review helpfulness", *Journal of Computer-Mediated Communication*, Vol. 20 No. 2, pp. 136–152.

- Racherla, P. and Friske, W. (2012), "Perceived 'usefulness' of online consumer reviews: An exploratory investigation across three services categories", *Electronic Commerce Research and Applications*, Vol. 11 No. 6, pp. 548–559.
- Racherla, P., Mandviwalla, M. and Connolly, D.J. (2012), "Factors affecting consumers' trust in online product reviews", *Journal of Consumer Behaviour*, Vol. 11 No. 2, pp. 94–104.
- Resnick, P. and Zeckhauser, R. (2002), "Trust among strangers in Internet transactions: Empirical analysis of eBay's reputation system", in *The Economics of the Internet and E-commerce*, Emerald Group Publishing Limited, pp. 127–157.
- Reuters, T. (2017), "InCites", available at: <https://jcr.incites.thomsonreuters.com> (accessed 27 November 2018).
- Robinson, R., Goh, T.-T. and Zhang, R. (2012), "Textual factors in online product reviews: a foundation for a more influential approach to opinion mining", *Electronic Commerce Research*, Vol. 12 No. 3, pp. 301–330.
- Ross, B., Jung, A.-K., Heisel, J. and Stieglitz, S. (2018), "Fake News on Social Media: The (In) Effectiveness of Warning Messages", *39th International Conference on Information Systems (ICIS)*, San Francisco, CA, USA, Vol. 39.
- Rubin, A. (2016), "Yelpers write 100 million reviews and counting", available at: <https://www.yelpblog.com/2016/03/yelp-100-million-reviews-and-counting> (accessed 15 September 2018).
- Ryang, H., Yun, U., Pyun, G., Lee, G. and Kim, J. (2015), "Ranking algorithm for book reviews with user tendency and collective intelligence", *Multimedia Tools and Applications*, Vol. 74 No. 16, pp. 6209–6227.
- Salehan, M. and Kim, D.J. (2016), "Predicting the performance of online consumer reviews: A sentiment mining approach to big data analytics", *Decision Support Systems*, Vol. 81, pp. 30–40.
- Schindler, R.M. and Bickart, B. (2012), "Perceived helpfulness of online consumer reviews: The role of message content and style", *Journal of Consumer Behaviour*, Vol. 11 No. 3, pp. 234–243.
- Schlosser, A.E. (2011), "Can including pros and cons increase the helpfulness and persuasiveness of online reviews? The interactive effects of ratings and arguments", *Journal of Consumer Psychology*, Vol. 21 No. 3, pp. 226–239.
- Scopus (2017), "CiteScore metrics for journals and serials", available at: <https://www.scopus.com> (accessed 27 November 2018).
- Shan, Y. (2016), "How credible are online product reviews? The effects of self-generated and system-generated cues on source credibility evaluation", *Computers in Human Behavior*, Vol. 55, pp. 633–641.
- Shen, X.-L., Zhang, K.Z.K. and Zhao, S.J. (2016), "Herd behavior in consumers' adoption of online reviews", *Journal of the Association for Information Science and Technology*, Vol. 67 No. 11, pp. 2754–2765.
- Singh, J.P., Irani, S., Rana, N.P., Dwivedi, Y.K., Saumya, S. and Roy, P.K. (2017), "Predicting the 'helpfulness' of online consumer reviews", *Journal of Business Research*, Vol. 70, pp. 346–355.
- Teng, S., Wei Khong, K., Wei Goh, W. and Yee Loong Chong, A. (2014), "Examining the antecedents of persuasive eWOM messages in social media", *Online Information Review*, Vol. 38 No. 6, pp. 746–768.
- TripAdvisor (2018), "Number of user reviews and opinions on TripAdvisor worldwide from 2014 to 2017 (in millions)", available at: <https://www.statista.com/statistics/684862/tripadvisor-number-of-reviews/> (accessed 25 November 2019).
- vom Brocke, J., Simons, A., Riemer, K., Niehaves, B., Plattfaut, R. and Cleven, A. (2015), "Standing on the shoulders of giants: Challenges and recommendations of literature search in information systems research", *Communications of the Association for Information Systems*, Vol. 37 No. 9, pp. 205–224.
- Weathers, D., Swain, S.D. and Grover, V. (2015), "Can online product reviews be more helpful? Examining characteristics of information content by product type", *Decision Support Systems*, Vol. 79, pp. 12–23.

- Webster, J. and Watson, R.T. (2002), "Analyzing the past to prepare for the future: Writing a literature review", *MIS quarterly*, Vol. 26 No. 2, xiii--xxiii.
- Willemsen, L.M., Neijens, P.C., Bronner, F. and Ridder, J.A. de (2011), "'Highly recommended!'" The content characteristics and perceived usefulness of online consumer reviews", *Journal of Computer-Mediated Communication*, Vol. 17 No. 1, pp. 19–38.
- Wu, P.F. (2013), "In search of negativity bias: An empirical study of perceived helpfulness of online reviews", *Psychology & Marketing*, Vol. 30 No. 11, pp. 971–984.
- Xu, Q. (2014), "Should I trust him? The effects of reviewer profile characteristics on eWOM credibility", *Computers in Human Behavior*, Vol. 33, pp. 136–144.
- Yang, S.-B., Hlee, S., Lee, J. and Koo, C. (2017a), "An empirical examination of online restaurant reviews on Yelp. com: A dual coding theory perspective", *International Journal of Contemporary Hospitality Management*, Vol. 29 No. 2, pp. 817–839.
- Yang, S.-B., Shin, S.-H., Joun, Y. and Koo, C. (2017b), "Exploring the comparative importance of online hotel reviews' heuristic attributes in review helpfulness: a conjoint analysis approach", *Journal of Travel & Tourism Marketing*, Vol. 34 No. 7, pp. 963–985.
- Yelp (2018), "Cumulative number of reviews submitted to Yelp from 2009 to 2017 (in millions)", available at: <https://www.statista.com/statistics/278032/cumulative-number-of-reviews-submitted-to-yelp/> (accessed 25 November 2019).
- Yin, D., Bond, S. and Zhang, H. (2013), "Anxious or angry? Effects of discrete emotions on the perceived helpfulness of online reviews", *MIS quarterly*, Vol. 38 No. 2, pp. 539–560.
- Yin, D., Mitra, S. and Zhang, H. (2016), "Research note—When do consumers value positive vs. negative reviews? An empirical investigation of confirmation bias in online word of mouth", *Information Systems Research*, Vol. 27 No. 1, pp. 131–144.
- Zhao, X., Wang, L., Guo, X. and Law, R. (2015), "The influence of online reviews to online hotel booking intentions", *International Journal of Contemporary Hospitality Management*, Vol. 27 No. 6, pp. 1343–1364.
- Zheng, X., Zhu, S. and Lin, Z. (2013), "Capturing the essence of word-of-mouth for social commerce: Assessing the quality of online e-commerce reviews by a semi-supervised approach", *Decision Support Systems*, Vol. 56, pp. 211–222.
- Zhou, S. and Guo, B. (2017), "The order effect on online review helpfulness: A social influence perspective", *Decision Support Systems*, Vol. 93, pp. 77–87.
- Zhu, L., Yin, G. and He, W. (2014), "Is this opinion leader's review useful? Peripheral cues for online review helpfulness", *Journal of Electronic Commerce Research*, Vol. 15 No. 4, pp. 267–280.