IS BEING HELPFUL GOOD ENOUGH FOR ONLINE REVIEWS? EXPLORING THE ROLE OF INFORMATION CREDIBILITY AND DATA SOURCE THROUGH META-ANALYSIS

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ABSTRACT

Electronic word of mouth (eWOM) plays a critical role in the contemporary online environment. Past studies mainly focused on the helpfulness of eWOM and explored its antecedents and consequences. However, fake reviews and manipulated reviews highlight a need to investigate the credibility of eWOM messages (information credibility). In addition, as the crawling data approach (secondary data) gets popular, different conclusions may be reach compared with traditional self-report primary data. We designed a meta-analysis that contains both meta-analytic structural equation modeling (MASEM) and bivariate meta-analysis to address these issues. The results first indicate the critical role of information credibility on eWOM induced decisions and then illustrate how the relationships between information helpfulness and its antecedents are contingent on data source.

Keywords: eWOM; Information credibility; Information helpfulness; Meta-analytic structural equation modeling; Data source

1. Introduction

Electronic word of mouth (eWOM) plays a critical role in the digital era. eWOM – such as consumer opinions, user experiences, and product reviews – not only serves as a source of information that influences human behavior but also brings unprecedented opportunities and challenges for corporate marketing activity (Cheng & Zhou, 2010; Floyd et al., 2014). Many consumers provide their comments on a product or a service on review-only sites (e.g., Yelp and TripAdvisor), social media (e.g., Facebook), and search engines (e.g., Google). The user-generated content is crucial in a web 2.0 environment because it facilitates trust-building and consumer decision-making. Uncertainties and risks are increased while shopping online since customers cannot directly experience the product or service (Hu et al., 2010; Liang & Huang, 1998). Building trust can effectively reduce perceived risk and is critical in online shopping (Kim et al., 2008; Pavlou, 2003)

eWOM is vital for trust-building since consumers consider comments from other consumers more credible than advertisements from the sellers (Cheung et al., 2009; Park et al., 2007). Most consumers search and review comments before making purchase decisions (Baek et al., 2012; Luo et al., 2014; Yan et al., 2016) or booking travel packages (Leong et al., 2019). From a practical perspective, whether those messages can reduce uncertainty and facilitate purchase decision-making is critical. Therefore, many researchers model information adoption behavior as an outcome of information helpfulness (IH) of the comments. They also explore how IH is affected by various features of the message. Since the impacts of those features are inconsistent in different studies, researchers, therefore, adopted a meta-analysis (MA) approach to explore the effects of message characteristics on IH under different conditions (e.g., Hong et al., 2017).

Even though these MA studies have laid a solid foundation for this research stream, some research opportunities remain. First, past studies have highlighted the importance of eWOM and the conditions that each antecedent of IH can take effect. However, it is arguable that the information adoption decision is not solely determined by helpfulness. Fake news or comments can be observed frequently on various platforms (Munzel, 2016). It is also not rare that the rating system may be manipulated by adding enormous positive or negative comments or ratings within a very short period (Hu et al., 2012). As an outcome, some platforms have developed mechanisms to screen and exclude those malicious attempts (Ivanova & Scholz, 2017). The above implies that, in addition to the helpfulness of information, the credibility of information (or information credibility) (IC) is another emerging critical antecedent of information adoption behavior (Cheung et al., 2012; Cheung et al., 2009; Luo et al., 2015; Luo et al., 2013; Luo et al., 2014). Since past MA studies only include IH as the determinant of information adoption decisions, our first research question is, "*RQ1: Should IC be included as another important antecedent of eWOM adoption decisions in the eWOM research?*"

Second, past MA addressed some interesting issues and illustrated that the focal relationships might be stronger or weaker under certain conditions (moderators). Possible moderators that have been identified include product type, industry type, culture-background, research method, measurement approach, platform, brand, culture, positivity degree (Babić Rosario et al., 2016; Hong et al., 2017; Purnawirawan et al., 2015; Wang et al., 2019; You et al., 2015). It is noticeable that, in addition to collecting data from the proposed studies by using experiment or survey methods, researchers gradually use existing data (secondary data) to validate the proposed relationships. Popular sources of secondary data include crawling data from the website, utilizing existing commercial databases, and adopting operational data from the platforms. Secondary data is different from primary data in many perspectives, such as direct-or-indirect measurement and sample size. As an outcome, the results based on secondary data may be inconsistent with those obtained using primary data. However, the source of data hasn't been included in the past MA studies. To answer the call by recent IS studies (e.g., Hong et al., 2017; Wang et al., 2019), this study explores whether the magnitude of the relationships between IH and its determinants is contingent on the source of data. Therefore, our second research question is "*RQ2: Whether the source of data moderates the relationships between IH and its antecedents in the eWOM studies?*"

Recently, the meta-analytic structural equation modeling (MASEM) approach has drawn significant attention. Unlike the traditional bivariate meta-analysis approach, which allows researchers to test whether the proposed relationship can be firmly observed under different conditions, this approach makes testing the nomological network possible. For example, Qahri-Saremi and Montazemi (2019) adopted this approach to describe how various factors affect the adoption of eWOM from a heuristic-systematic perspective. However, even though this approach allows researchers to explore the relationships among various paired factors, the traditional bivariate meta-analysis approach still has its advantages, such as explaining whether one link can be better observed under certain conditions. Therefore, combining these two approaches can benefit related research streams by showing the nomological network from a theoretical perspective and revealing whether the focal relationships are held under different conditions. Therefore, we first attempt to explore the importance of IC by using MASEM. Based on the above argument, we suspect that IC is no less critical than IH in an eWOM context. Second, we attempt to explore the impact of data source on the relationships between IH and its antecedents.

By answering the above questions and reaching the listed goals, this study contributes to eWOM literature in the following ways. First, we highlight the role of IC by showing its impact on eWOM adoption decisions. This is done by exploring its nomological net with MASEM. Second, with traditional bivariate meta-analysis, we contribute to eWOM studies by showing the impact of moderators that haven't been explored before. Specifically, we showed that data source as a moderator for IH and its antecedents. The rest of this study is organized as the following. We first reviewed the research of eWOM and the often adopted theoretical frameworks. Based on the MASEM approach, we first build hypotheses based on the nomological net of IC. Based on the traditional bivariate meta-analysis approach, we then hypothesize possible moderators of the relationships between IH and its antecedents. The third section describes the research methods adopted for this study. The fourth section contains both the MASEM and the traditional bivariate meta-analysis result. The last section addresses the conclusions and discussions of this study.

2. Theoretical Framework

2.1. Overview of eWOM Research

WOM is person-to-person non-commercial communication between a receiver and a communicator, regarding a brand, product, service, or organization (Arndt, 1967). With the growth of the Internet, WOM takes place in an online form and is named electronic word-of-mouth (eWOM). Hennig-Thurau et al. (2004) described eWOM as "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet." On the internet, people share their opinions, comments and reviews exchanged through a variety of means such as online forums, online blogs, online review sites, electronic bulletin board systems, and social networking sites (Cheung & Lee, 2012; Hennig-Thurau et al., 2004). While eWOM and traditional WOM share several common attributes, they are different from each other in some ways (Cheung & Thadani, 2012). For instance, eWOM has a higher speed of diffusion. It is also more persistent, accessible, and measurable than traditional WOM.

eWOM has become an important topic to researchers and e-commerce practitioners in the information system (IS) area since the early 2000s (Jabr et al., 2020). These scholarly endeavors have resulted in a growing body of eWOM literature and tackled a variety of research questions dealing with the eWOM effect, such as IC, IH, behavioral intention, information adoption, customer attitude, and product sales (Cheung & Thadani, 2012; Ismagilova et al., 2017). eWOM studies mainly model the causal relationship based on the sequence listed in Table 1. eWOM characteristics affect the persuasiveness of eWOM, which, in turn, generate eWOM adoption decisions. Examples of these eWOM characteristics include content-related factors, source-related factors, and social endorsement-related factors. The persuasiveness of eWOM includes IC and IH. eWOM adoption decisions mainly focus on behavioral intention, information adoption, customer attitude, and product sales.

However, even though the number of studies has increased significantly, confusion also increases since some of these eWOM studies reached contradictory and inconsistent findings. Researchers explored the conflicting results with a MA approach to identify possible contingent factors of the impacts of eWOM characteristics. The goal of those studies is to offer guidance on the selection of variables and research methods for future studies. Early MA studies on eWOM are mainly in the marketing area. These studies examined the impacts of review volume and review valence on sales effects under different types of reviewers, websites, and product types (Babić Rosario et al., 2016; Floyd et al., 2014; You et al., 2015). Later on, researchers adopted this approach to clarifying the mixed findings of a specific independent variable (e.g., review valence and source credibility) on various psychological outcomes (Ismagilova et al., 2020; Purnawirawan et al., 2015). For instance, Purnawirawan et al. (2015) found that message valence positively affects attitude, especially when the brand is unfamiliar. Also, message valence has no significant influence on IC but has a positive effect on IH. In addition, researchers also investigated variables that change eWOM adoption decisions and clarified the mixed findings related to the determinants, especially IH (Hong et al., 2017; Wang et al., 2019). For example, Hong et al. (2017) found that reviewer's personal information and expert labels exert a substantial impact on IH. Review rating has a positive relationship when IH is measured by helpful vote, or the data is obtained from retailers-hosted platform and experience product situation. Wang et al. (2019) found that experience product review volume, length, and rating positively influence IH. Also, if the existing data is obtained from Amazon.com, review volume negatively affects IH. Interestingly, Hong et al. (2017) showed that readability does not affect IH, while Wang et al. (2019) identified readability as a critical antecedent.

Even though past MA studies built a solid foundation for understanding eWOM adoption decisions, some issues are still noticeable. The first one is that most eWOM research adopted a practical perspective and considered information helpfulness a major antecedent of information adoption. However, the importance of IC has been highlighted by several studies recently. IC refers to the extent to which the eWOM is believable. Social media is one important information source, and IC is crucial for sensitive information, such as food safety (Cui et al., 2019) or health information (Fan et al., 2013). Tan and Lee (2019) even named the social media-based eWOM as sWOM and argued the importance of sWOM credibility on sWOM adoption. Another reason for IC gaining its weight is fake reviews. Some sellers or buyers adopted various approaches to manipulate the rating score and provide fake online reviews to boost or inhibit potential purchases (Chang et al., 2015). Fake online review issues, therefore, draw consumers' attention (Munzel, 2016). Therefore, as suggested by Luo et al. (2015), IC is the most critical factor in eWOM adoption. Even though IC attracts some attention, almost all the focus goes on the importance of IH while attempting to predict the eWOM adoption decisions.

Table 1: The Relationship Diagram of the Impact of eWOM Communication

	Constructs	**Definition or measurement**
eWOM characteristics	Content	The eWOM written by the reviewer (Cheung & Thadani, 2012).
	Source	The person who writes the eWOM (Cheung & Thadani, 2012).
	Social endorsement	The inclination towards the ideas or behaviors of other people without much scrutiny of the content or source (Hilligoss & Rieh, 2008; Metzger & Flanagin, 2013).
eWOM Persuasiveness	Information credibility (IC)	The degree to which an individual perceives the recommendation from others as believable, true, or factual (Cheung et al., 2009; Ismagilova et al., 2017).
	Information helpfulness (IH)	The degree to which the information assists consumers in avoiding uncertainties to make their purchase decisions (Davis, 1989; Ismagilova et al., 2017).
eWOM adoption decisions	Behavioral intention	The probability or willingness to take action (e.g. purchasing products or visiting sites) (Ismagilova et al., 2017).
	Information adoption	The extent to which individuals accept and use eWOM communications in making decisions (Cheung & Thadani, 2012; Ismagilova et al., 2017; Sussman & Siegal, 2003).
	Customer attitude	Reviewer's overall evaluation of a person, objects (e.g., brand/products/websites) and issues (Cheung & Thadani, 2012).
	Product sales	The treatment of sales measures (Floyd et al., 2014) mainly can be separated into (1) Measures directly related to sales (e.g. gross receipts or rating points); (2) Proxy measures of sales (e.g. product sales rankings); (3) Measures of relative sales (e.g. the result from the econometric technique of differencing).

Another issue is that most MA studies of eWOM were conducted with the bivariate method because it allows researchers to explore possible moderators for the given relationships. However, bivariate MA only considers bivariate relationships and potential moderators. It cannot verify the nomological network of variables contained in one theory. Recently, an approach combining covariance-based structural equation modeling (SEM) and MA approach has been proposed, named MASEM. MASEM can better assess structural parameters and bolster the statistical power of model tests (Jak & Cheung, 2020; Viswesvaran & Ones, 1995). Qahri-Saremi and Montazemi (2019) used MASEM to explore whether heuristic cues or systematic cues are more associated with IH by modeling it as the only antecedent of eWOM message adoption. Their results show that the effect of heuristic cues (i.e., source trustworthiness) on the IH is fully mediated by its effects on systematic cues (i.e., information quality and IC). Moreover, based on the total effect analysis, they also suggested that IC might be a critical factor toward message adoption. However, a lack of a direct link from IC to message adoption in their model leave this issue unresolved. Based on the above review, there is a need to investigate the role of IC on eWOM adoption decisions. Therefore, we take advantage of both bivariate meta-analysis and the MASEM approach. Next, we will build the nomological network and develop our hypothesis.

2.2. Theoretical Development

Dual-process theories have been one of the most widely used models to explain eWOM communications in IS discipline (Cheung et al., 2008). There are two well-known dual-process theories: elaboration likelihood model (ELM) and heuristic-systematic model (HSM). These theories take a similar perspective to explain how people process information, establish its validity assessments, and later form decisions (Eagly & Chaiken, 1993). However, there are two significant differences (Angst & Agarwal, 2009). First, HSM argues that heuristic processing can jointly act with systematic processing but ELM suggests that persuasion can simultaneously act through a central and peripheral route. Second, different from ELM that has been empirically tested widely, there is limited empirical support for HSM. For example, Cheung and Thadani (2012) summarized prior eWOM communication studies and found that ELM is the most commonly used theory. In addition, this theory has been widely adopted in several domains to understand the effects of various information cues (Angst & Agarwal, 2009). We therefore follow past studies and adopt ELM as our theoretical framework. Through the lens of ELM (see Figure 1), we examine whether the impacts of eWOM characteristics on eWOM adoption decisions go through two eWOM persuasiveness attributes (RQ1). In addition, we also employed data source (survey data as primary and crawled data as secondary) as a moderator on the relationships between eWOM characteristics and IH (RQ2).

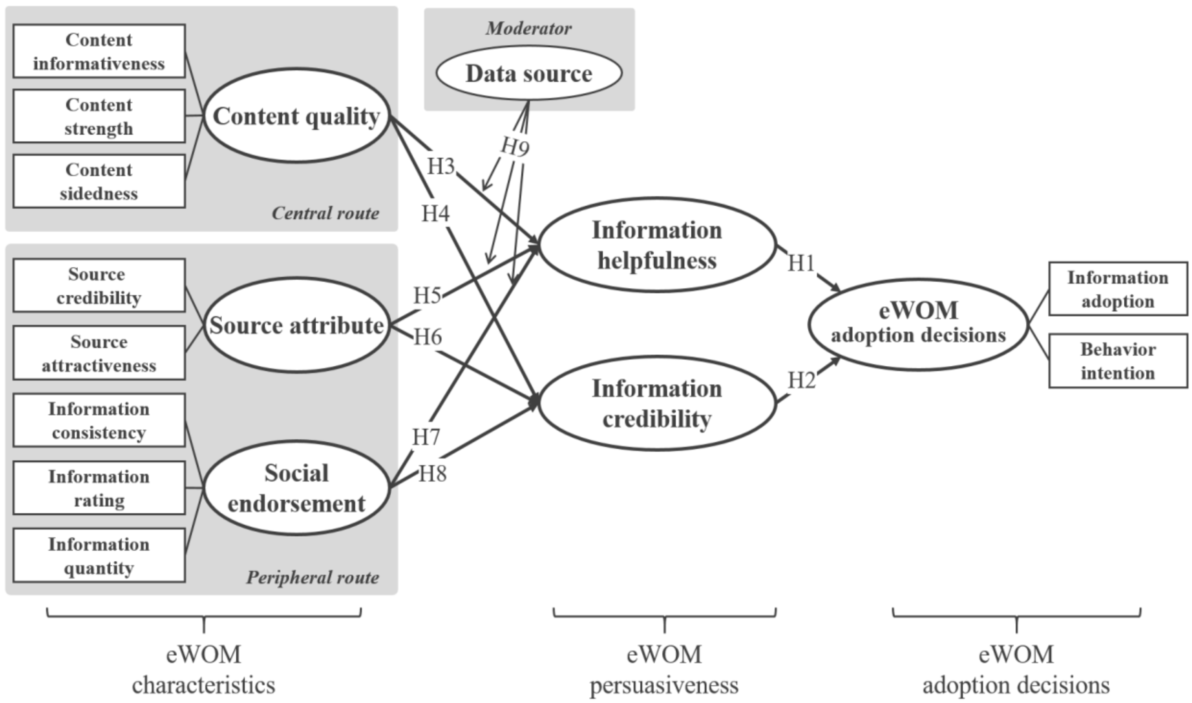

Figure 1: Proposed Electronic Word of Mouth (eWOM) Adoption Decisions Model

2.2.1. Persuasiveness of eWOM

Information helpfulness is a fundamental predictor of eWOM adoption decisions. Information helpfulness (also known as information diagnosticity) refers to the degree to which the information assists consumers in avoiding uncertainties (e.g., alternative choices, judgments, or categorizations of the decision object) to make their purchase decisions (Davis, 1989; Ismagilova et al., 2017). Sussman and Siegal (2003) extended information usefulness proposed by Davis (1989) to the computer-mediated communication context and argued its importance on information adoption. It is argued that purchasing or visiting intentions toward merchants suggested by others in the reviews is higher when consumers find that the recommended information is useful (Bae et al., 2017; Filieri et al., 2018a; Xiao & Li, 2019; Xu et al., 2015). Actually, most studies that applied this concept confirmed the positive and direct impact of IH on message adoption (Bae et al., 2017; Cheung et al., 2008; Yan et al., 2016). Thus, we hypothesize the following.

Hypothesis 1. *IH is positively associated with eWOM adoption decisions.*

Information credibility is another important antecedent of eWOM adoption decisions. Information credibility (also known as information believability) refers to the degree to which an individual perceives the recommendation from others as believable, true, or factual (Cheung et al., 2009; Ismagilova et al., 2017). To clarify, IC focuses on the information itself in this study, not trusting beliefs about a person or a platform. Wathen and Burkell (2002) pointed out that whether receivers perceive the information as credible is crucial during the information persuasion process in an offline context (Smith & Vogt, 1995). This process also can apply to the online context, such as online reviews or recommendations. For example, Cheung et al. (2009) indicated that perceived IC is a primary concern of online consumer review adoption. Based on the dual-process theory proposed by Deutsch and Gerard (1955), they also explore how IC is affected by different types of influences (informational and normative determinants). Many studies have found empirical support for the relationship between IC and information adoption (Bae et al., 2017; Fang, 2014; Luo et al., 2013). Furthermore, IC is associated with other consumer behaviors, such as purchase decisions (Bae et al., 2017; Thomas et al., 2019; Xu et al., 2015). Thus, we hypothesize the following.

Hypothesis 2. *IC is positively associated with eWOM adoption decisions.*

2.2.2. From eWOM Characteristics to eWOM Persuasiveness

ELM argues that individuals do not always elaborate information with high cognitive effort. Instead, they sometimes process the information quickly with heuristic and simple decision rules (Bhattacherjee & Sanford, 2006). This suggests that a decision-maker may assess the persuasiveness of the incoming information through two routes and make the decision based on the evaluated result. The central route is rational elaboration, while the peripheral route is intuitive and affective. Furthermore, different information cues may trigger the use of each route differently (Bhattacherjee & Sanford, 2006; Petty & Cacioppo, 1986). eWOM communication literature provides a wide range of theoretical foundations employed in a variety of eWOM characteristics. As shown in Table 2, we separated these eWOM characteristics based on the central route (content quality) and peripheral route (source attribute and social endorsement).

According to the ELM, the quality of content is critical when the central route is adopted (Petty & Cacioppo, 1986; Sussman & Siegal, 2003). People evaluate the products or services based on their digested results of the information content. The arguments need to be logically and factually convincing to enact a change of attitude (Bhattacherjee & Sanford, 2006). Researchers have indicated that informative and persuasive content can lead to favorable decision outcomes (Angst & Agarwal, 2009). Thus, we focus on content quality and treated it as the central cue of eWOM in this study. However, when people are either unable or unwilling to process the arguments presented in a message, they tend to shift their attention to peripheral cues (i.e., heuristics cues) to reduce cognitive load (Petty & Cacioppo, 1986; Sussman & Siegal, 2003). The source's credibility, expertise, and trustworthiness have been suggested as critical peripheral cues in traditional ELM literature. In the eWOM context, people can evaluate the status of a single reviewer (source credibility) and the pooled results generated by social aggregation mechanisms (e.g., averaged score). Since past studies utilized different terms, we combined the used concepts and outlined two types of peripheral cues of eWOM: source attribute and social endorsement.

2.2.2.1. Central Routes in the Antecedent of Persuasiveness

Content is the eWOM written by the reviewer (Cheung & Thadani, 2012). However, since there is no standard format for comment composition, the length of the comment varies from short to long, and the content may be objective descriptions or subjective expressions. Sometimes it even includes both positive and negative valence simultaneously in one review (Park et al., 2007). When researchers include content quality in their models, they therefore conceptualize or operationalize it differently. For example, Kim and Benbasat (2009) manipulated arguments into different strength levels in their experiment-based study. Another example is that some studies assess information quality based on the criteria proposed by DeLone and McLean (2003), which is used to evaluate the information contained in information management systems (Cheung et al., 2008; Cheung & Thadani, 2012; Nelson et al., 2005; Park et al., 2007). Zhang et al. (2014) therefore proposed that content quality should include content informativeness and content strength. However, in addition to content strength, Mongeau and Stiff (1993) pointed out the need to include content valence. Lee and Xia (2011) also considered content quality as the valence of thoughts evoked by a message. To fully capture the concept of content quality suggested in the literature, we therefore treat content quality as a multidimensional construct, which contains *content informativeness*, *content strength*, and *content sidedness*.

Content informativeness represents the quality of the content from the perspective of information characteristics (Cheung et al., 2008; Cheung & Thadani, 2012; Nelson et al., 2005; Park et al., 2007). Based on the concept of information quality (DeLone & McLean, 1992) and attributes of eWOM, we included four dimensions in this construct: (1) comprehensiveness, (2) accuracy, (3) relevance, (4) timeliness. Comprehensiveness can be represented by the richness of the content (i.e., length) and the ease of reading (i.e., readability) (Kuan et al., 2015; Mudambi & Schuff, 2010). It reflects whether the messages are understandable, complete, and informative with breadth and depth. Accuracy is high when the message is accurate, correct, and reliable. Relevance represents the extent to which the statements are applicable, relevant, and appropriate. Timeliness focuses on the number of days/weeks elapsed (Guo & Zhou, 2017; Zhu et al., 2014) and reflects whether the messages are current, timely, and up-to-date. Content informativeness is expected to be associated with persuasiveness. For example, prior research has empirically confirmed that content quality can positively affect people’s perceptions of IH (Lee & Hong, 2019; Xiao & Li, 2019) and IC (Thomas et al., 2019).

Content strength is defined as the persuasive strength or plausibility of arguments embedded in an informational message (Bhattacherjee & Sanford, 2006; Eagly & Chaiken, 1993). A strong argument is convincing, sound, reasonable, and effectively supported (Zhang, 1996). Most lab experiment research treated content strength as an independent variable and manipulated this construct by composing the message with various subjective probabilities or substantiation of claims (Eagly & Chaiken, 1993; Kim & Benbasat, 2006). Prior research has empirically confirmed that content strength can positively affect the IH (Luo et al., 2018) and IC (Cheung et al., 2012; Cheung et al., 2009; Fang, 2014; Luo et al., 2015; Luo et al., 2014).

Content sidedness is defined as the extent to which both positive and negative viewpoints (two-sided) are contained in one message, which is different from one-sided framed information (Cheung et al., 2012; Yan et al., 2016). Except for few studies that considered this construct a peripheral factor, such as Cheung et al. (2012), most recent research treated it as a central factor (Luo et al., 2015; Luo et al., 2014). Content sidedness has a significant impact on judgments. People can scrutinize information through content valence and then predict possible behavioral outcomes and infer causality (Lee & Xia, 2011; Luo et al., 2015; Luo et al., 2014). Therefore, users can easily make a decision when information is clearly positioned. Furthermore, it is noticeable that many messages focus on one side only. Overemphasizing the positive outcomes (of buying a product) does not necessarily result in an expected decision (e.g., purchase) since readers may question its reality. Instead, people consider a message that contains both positive and negative comments more credible (Cheung et al., 2012). We thus hypothesized the following.

Hypothesis 3. *Content quality is positively associated with IH.*

Hypothesis 4. *Content quality is positively associated with IC.*

2.2.2.2. Peripheral Routes in the Antecedent of Persuasiveness

Source attribute focuses on the characteristics of information communicators (Hilligoss & Rieh, 2008; Hovland et al., 1953; Sussman & Siegal, 2003). Compared with an unfamiliar source, people are more likely to trust a source that they can recognize (Metzger & Flanagin, 2013). A credible source contains three characteristics: credible, physically attractive, and ideologically similar (Wilson & Sherrell, 1993). On a social network site, decision-makers can evaluate various characteristics of reviewers, such as connections, profile information, and posting activity (Fang, 2014). Since source similarity is not broadly discussed in the IS area, only *source credibility* and *source attractiveness* are retained to represent source-based peripheral cues in this study.

Source credibility is defined as the extent to which an information source is perceived to be believable, competent, and trustworthy by information receivers (Cheung & Thadani, 2012; Petty & Cacioppo, 1986). Different from IC that focuses on the recommendations of the message, source credibility focuses on the people who provide the recommendations (Appelman & Sundar, 2016; Metzger et al., 2003). Source credibility has been widely studied as a crucial peripheral cue in the eWOM context. It consists of two dimensions: expertise and trustworthiness (Hovland et al., 1953; Petty & Cacioppo, 1986). Source expertise reflects the amount of knowledge, skill, and experience an individual has about a domain (Fang, 2014; Ohanian, 1990). Consumers may assess the source expertise of reviewers by referring to the duration of their membership, the number of reviews they posted, and their credentials (e.g., the “Elite” badge on Yelp or the “Top 10,000 Reviewer” badge on Amazon) (Filieri et al., 2018a; Racherla & Friske, 2012; Zhang et al., 2014; Zhu et al., 2014). Source trustworthiness reflects the extent to which an individual is reliable, unbiased, and honest (Ohanian, 1990). One indicator of trustworthiness is whether reviewers provide detailed information about themselves, such as profile picture, real name, origin, and lifestyle (Filieri, 2016). In addition, prior research has shown the impact of source credibility on IC (Cheung et al., 2012; Fang, 2014; Luo et al., 2015; Luo et al., 2014), and IH (Cheung & Thadani, 2012).

Source attractiveness, in general, is represented by tie strength, defined as the potency of the bond between members of a network. It also shows the closeness of the relationship between the receiver and the source (Chu & Kim, 2011; Mittal et al., 2008). In a social networking context, source attractiveness can be evaluated by the social structural information (e.g., the number of followers and friends), the frequency of social contact, the type of social relation, and the intimacy between two parties, etc. (Zhu et al., 2014). Theoretically, an attractive communicator can generate more influence on the message receivers (Fang, 2014). Past studies have empirically shown that source attractiveness is positively associated with IC (Tan & Lee, 2019) and IH (Guo & Zhou, 2017; Zhu et al., 2014). We thus hypothesized the following.

Hypothesis 5. *Source attribute is positively associated with IH.*

Hypothesis 6. *Source attribute is positively associated with IC.*

Social endorsement refers to the inclination towards the ideas or behaviors of other people without much scrutiny of the content or source (Hilligoss & Rieh, 2008; Metzger & Flanagin, 2013). In this study, we considered *information consistency*, *information linear rating/extreme rating*, and *information quantity* as social endorsement-related peripheral cues because they are related to acts performed by the majority. For information consistency, consumers can actively validate information across different sources and check the consistency in the eWOM context (Metzger & Flanagin, 2013). In a social community, members are easily affected by others and tend to follow the majority (Deutsch & Gerard, 1955; Metzger et al., 2010). People may also be wittingly or unwittingly influenced by cumulative review volume or star rating (Cheung et al., 2009; Duan et al., 2008). Therefore, information rating and information quantity should be included.

Information consistency is defined as the extent to which the viewpoint of a message is consistent with other messages (Barry & Schamber, 1998). Information consistency is a critical peripheral cue in the eWOM context (Baek et al., 2012; Cheung et al., 2012; Luo et al., 2015; Luo et al., 2014; Zhu et al., 2014). Plenty of online reviews are submitted and read on eWOM forums daily. Consumers can quickly scan the consistency between information obtained from different sources (Cheung & Thadani, 2012; Cheung et al., 2012). High consistency implies that many consumers have shared experiences or viewpoints. Theoretically, the viewpoint is more trustworthy when it is consistent with others. Empirically, the impact of information consistency on IC has been examined broadly (Cheung et al., 2012; Cheung et al., 2009; Luo et al., 2014).

Linear rating is defined as the overall valence of current information given by previous readers, usually displayed by a star icon (Cheung et al., 2009; Thomas et al., 2019; Yan et al., 2016). Most websites provide a rating mechanism that can aggregate answers from a number of consumers (who approve or disapprove of service performance) as a collective recommendation (Thomas et al., 2019; Yan et al., 2016). Information rating has been considered a peripheral cue in the eWOM context (Baek et al., 2012; Luo et al., 2015; Luo et al., 2014; Zhu et al., 2014). Prior research has examined the relationship between information rating and IC (Cheung et al., 2009; Fang, 2014; Luo et al., 2014; Thomas et al., 2019) and also showed that information rating has a positive effect on IH (Korfiatis et al., 2012).

Extreme rating is in the form of star-rating (e.g., one star or five stars) and is measured with the difference between each review score and the averaged score (Cao et al., 2011). This construct mainly appears in those secondary data-based studies. Since most of the review process adopts a five-point star scale, a significant portion of reviewers tends to give a moderate rating unless they are extremely happy or unhappy with the product or service (Korfiatis et al., 2012). Kuan et al. (2015) indicate that extreme ratings are more visually distinct and more likely to be noticed, but they are less likely to be considered helpful. However, most research has demonstrated that reviews with higher rating extremity positively affect IH (Wang et al., 2019; Yan et al., 2016).

Information quantity is defined as the number of online reviews published on the platform (Cheung et al., 2008; Sicilia & Ruiz, 2010; Teng et al., 2017b). Most commerce platforms provide the number of people who have purchased the product and the number of reviews provided for each product. With such numerical information, consumers can easily recognize the popularity of a specific product (Filieri et al., 2018a). Information quantity has been considered a peripheral cue in the eWOM context (Baek et al., 2012; Park et al., 2007; Teng et al., 2017b; Xiao & Li, 2019; Yan et al., 2016). The level of popularity is a good indicator because it shows the sales performance and implies the quality of the product or service (Duan et al., 2008). In addition, prior research has shown the positive impact of information quantity on IH (Filieri et al., 2018b; Yan et al., 2016). We thus hypothesized the following.

Hypothesis 7. *Social endorsement is positively associated with IH.*

Hypothesis 8. *Social endorsement is positively associated with IC.*

2.2.3. The Moderating Effect of Data Source on the Relationships between IH and Its Antecedents

The number of user reviews increased dramatically and caused an information overload problem. In addition, spamming reviews decrease decision-making efficiency (Hong et al., 2017). Thus, researchers and practitioners are curious why some messages are better accepted by consumers than others. To answer this question, Sussman and Siegal (2003) extended perceived usefulness to a computer-mediated communication context and coined it as perceived helpfulness. Following studies adopted a survey approach and measured IH with the developed self-report scale (Davis, 1989; Sussman & Siegal, 2003). On the other hand, many platforms (such as Amazon and Yelp) adopt social voting mechanisms and ask people to rate the helpfulness of one message (Hong et al., 2017). The growth of consumer-generated content drives researchers to capture IH with existing data (secondary data), such as "the ratio of helpful votes to total votes" (Mudambi & Schuff, 2010) and "the absolute total number of helpful votes" (Racherla & Friske, 2012; Zhu et al., 2014). A recent meta-analysis showed that the impacts of reviewers' characteristics and review rating on IH are different when IH is measured with the absolute number or relative ratio (Hong et al., 2017).

However, past MA largely ignored the difference between self-report survey (primary) and crawled data (secondary). First, self-report data captured personal experiences, and crawled data is based on actual transactions. Due to the resource limitation, the final sample size is much smaller when researchers attempt to collect self-report data. In contrast, all data available on the platform can be crawled with a software robot, and the resulting sample size is much bigger. According to the basic statistical concept, the level of significance varies as the sample size changes (Hair et al., 2019). It is easy for a small coefficient to be significant with a large sample size. Second, the self-report approach measures the overall experiences (perceptions and behavioral intention) with carefully developed multiple items that can better capture the desired concept. On the other hand, when data is crawled from the platform, researchers select proxy variables that may capture part of the intended concepts only. The predicting power may be lower under this context. Therefore, it is critical to understand whether the focal relationships are more likely to be supported (or stronger) under one condition. Researchers can then pick a better approach based on the goals of the paper. Therefore, we investigate the moderating effect of data source. We suspect that stronger relationships can be observed when primary data is collected (e.g., Hedges & Olkin, 2014; Santini et al., 2020). We thus hypothesized the following.

Hypothesis 9a. *Data source moderate the relationships between content quality and IH.*
Hypothesis 9b. *Data source moderate the relationships between source attribute and IH.*
Hypothesis 9c. *Data source moderate the relationships between social endorsement and IH.*

Table 2: Major Determinants in Existing Studies

	Determinant definition or measurement	Related construct
Factors related Central routes		
Content quality	**Content informativeness** The quality of the content from the perspective of information characteristics (Cheung et al., 2008; Cheung & Thadani, 2012; Park et al., 2007).	
	▪ **Comprehensiveness** reflects the messages are understandable, complete and informative with breadth and depth.	length, readability
	▪ **Accuracy** reflects the messages are accurate, correct, and reliable.	
	▪ **Relevance** reflects the messages are applicable, relevant and appropriate.	
	▪ **Timeliness** reflects the messages are current, timely, and up-to-date.	currency, age
	Content strength The persuasive strength or plausibility of arguments embedded in an informational message (Bhattacherjee & Sanford, 2006; Eagly & Chaiken, 1993).	
	Content sidedness The information that discusses both positive and negative viewpoints (Cheung et al., 2012; Yan et al., 2016).	two-sided, integrity
Factors related peripheral routes		
Source attribute	**Source credibility** The extent to which an information source is perceived to be believable, competent, and trustworthy by information receivers (Cheung & Thadani, 2012; Petty & Cacioppo, 1986). ▪ **Source expertise** reflects the amount of knowledge, skill, and experience an individual has about a domain (Fang, 2014; Ohanian, 1990). ▪ **Source trustworthiness** reflects the extent to which an individual is reliable, unbiased, and honest (Ohanian, 1990).	
	Source attractiveness The potency of the bond between members of a network (Chu & Kim, 2011; Mittal et al., 2008).	tie strength, social connectedness
Social endorsement	**Information consistency** The extent to which the viewpoint of a message is consistent with other messages (Barry & Schamber, 1998).	conformity, consensus
	Information rating (linear rating) The overall valence of current information given by previous readers (Cheung et al., 2009; Thomas et al., 2019; Yan et al., 2016). ▪ **Rating extremity** measured with the difference between each review score and the averaged score (Cao et al., 2011).	
	Information quantity The number of online reviews published on the platform (Cheung et al., 2008; Sicilia & Ruiz, 2010; Teng et al., 2017b).	volume, popularity

3. Research Methodology

3.1. Meta-analysis Approach

Meta-analysis (MA) serves as a powerful alternative or supplement to traditional literature reviews for research synthesis and has tackled various research questions in the IS discipline (Eden, 2002; Jeyaraj & Dwivedi, 2020). By integrating the results from multiple independent studies on the same relationship into a single estimate, MA assists researchers in finding a common truth behind conceptually similar studies and extracting new insights into the underlying relationship within the research area (Gurevitch et al., 2018; Hunter & Schmidt, 2004).

Structural equation modeling (SEM) is a frequently used multivariate technique to validate theoretical models (Hershberger, 2003) and test models containing complex relationships among variables. Based on the individual benefits of MA and SEM, researchers are suggested to use meta-analytic structural equation modeling (MASEM) to test the theory with data from multiple studies (Brown & Peterson, 1993). One advantage of MASEM is that it does not require all relationships to be included in each primary study. It estimates true correlations between variables of interest to create a pooled correlation matrix through MA, which can be used to fit in SEM (Viswesvaran & Ones, 1995).

We adopted both MASEM and bivariate meta-analysis approach in this study. To answer RQ1, we conducted both MASEM (Analysis 1) and bivariate meta-analysis (Analysis 2). For Analysis 1, we employed a random-effect two-stage structural equation modeling (TSSEM) technique proposed by Cheung (2015), and implemented it in R (programming language). The random-effects TSSEM technique is a statistical method that synthesizes multiple correlation matrices among the interest variables from multiple studies to create a pooled correlation matrix for running SEM and testing proposed hypotheses (Cheung, 2015). For Analysis 2, we conducted comparisons among key sub-dimensions of antecedents of IC and IH through MA. To answer RQ2, we conduct a bivariate meta-analysis (Analysis 3) to explore the moderating effect of data source on the relationships between IH and its antecedents.

3.2. Research Procedure Workflow

Figure 2 shows our analysis procedure workflow, which includes (1) literature identification and collection, (2) inclusion criteria, (3) article coding. Specifically, MASEM was adopted to understand the importance of IC (Analysis 1), and comparison analysis with a bivariate meta-analysis approach was used to clarify the contributions of eWOM characteristics on both IC and IH (Analysis 2). The bivariate meta-analysis approach was also used to clarify the moderating effect of the data source (Analysis 3).

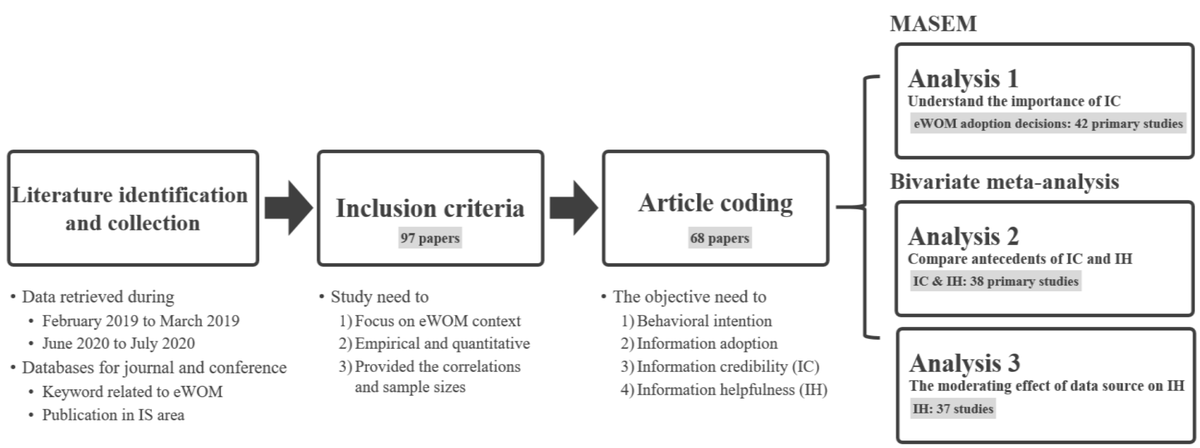

Figure 2: Research Analysis Procedure Workflow

3.2.1. Literature Identification and Collection

Identifying the source documents is a critical stage, for the set of source documents must be as large as possible to cover all the development within the theory. We conducted a comprehensive search of the extant eWOM literature in the IS area to identify and synthesize the primary empirical eWOM studies applicable to our methodological approach. During the periods from February 2019 to March 2019 and from June 2020 to July 2020, we used different combinations of search terms related to eWOM adoption decisions in the body of the papers, including “Electronic word of mouth”, “Online word of mouth”, “eWOM”, “online review”, “Internet word of mouth”, "user-generated content", "consumer review", “online recommendation”, “information adoption”, “eWOM adoption”, “information helpfulness”, “review helpfulness”, “eWOM helpfulness”, “information diagnosticity”, “review diagnosticity”, “information credibility”, “review credibility”, “eWOM credibility”. These terms allowed us to search across literature in the IS area. We searched a comprehensive set of databases for various journals and conference proceedings, such as Web of Science, EBSCO, JSTOR, Google Scholar, and Association for Information Systems eLibrary.

3.2.2. Inclusion Criteria

We adapted Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher et al., 2015) and established eligibility criteria that follows these rules: (1) the study's focus is on eWOM context; (2) the study was empirical and quantitative, and (3) the study provided the correlations and sample sizes required for MA. To ensure the reliability of our assessments, we excluded the papers that did not match the inclusion criteria. Our literature search finally resulted in a pool of 97 papers published between 2008 and 2020.

3.2.3. Article Coding

To ensure the reliability of our assessments, we separately assessed the 97 papers and resolved disagreements by adopting a consensus approach. According to Table 1 above, eWOM adoption decisions include behavioral intention, information adoption, customer attitude, and product sales. However, customer attitude was defined and measured differently (e.g., person, objects, issues, etc.). Besides, most of the articles that contain product sales do not provide a correlation matrix. We thus excluded customer attitude and product sales from the following analyses and mainly focused on behavioral intention, information adoption, IC, and IH. Finally, the data pool consists of 68 papers (see APPENDIX A).

For Analysis1, we included the papers that contain eWOM adoption decisions (i.e., behavioral intention and information adoption) as outcome variables. This procedure reduced our pool to 38 articles. Furthermore, to ensure that one study only includes a unique sample, we treated papers that provided two different datasets as two different studies (e.g., Tan & Lee, 2019; Teng et al., 2017a). Conversely, we retained only one study if two or more studies used the same dataset with the same factors (e.g., Cheung et al., 2009; Rabjohn et al., 2008). We identified 42 unique empirical studies related to eWOM information adoption through this process. To assure that all constructs are operationalized correctly, two authors independently assessed the conceptual and measurement of constructs in each of the 42 studies and assigned those constructs to the proposed eWOM adoption decision model. The third author joined the discussion for all inconsistencies. In this process, measurement items used to capture the construct are the focus instead of labels assigned to the constructs by the authors. The reason is that, although the labels assigned by different authors may vary, the concept captured by similar items should be similar and should be synthesized under the same factor (Qahri-Saremi & Montazemi, 2019). Moreover, we extracted correlations and sample size information related to the constructs. Finally, we extracted 207 correlations from 42 primary studies that comprise 10,583 samples.

For Analysis 2, we included the papers which focused on IC, IH, or both. We repeated the steps taken in Analysis 1 and assessed the consistency of concept and measurement for all in antecedents of IC and IH. Finally, we extract 124 correlations from 38 studies that comprise 10,015 samples.

For Analysis 3, we repeated the steps taken in Analysis 1 and assessed the consistency of concept and measurement for all antecedents of IH (primary and secondary data). This process resulted in a dataset containing 37 studies, comprising 1,375,849 sample sizes and 180 correlations with respective independent variables.

4. Meta-analysis Results

4.1. Analysis 1: Understand the Importance of IC

We adopted Meta-analytic structural equation modeling (MASEM) to understand the importance of IC in Analysis 1. We followed the two-stage procedure of the random-effects model of TSSEM (Cheung, 2015; Qahri-Saremi & Montazemi, 2019) to test our proposed eWOM adoption decision model.

4.1.1. Measures to Address Methodological and Statistical Artifacts

In the first stage of TSSEM, we followed the guideline indicated by Hunter and Schmidt (2004) and steps recommended by Qahri-Saremi and Montazemi (2019) to address the potential issues caused by methodological and statistical artifacts while pooling our data for TSSEM. In this stage, we assessed (1) multicollinearity, (2) publication bias, and (3) heterogeneity. First, multicollinearity defies the pre-assumption of independence of constructs in SEM and should be excluded. Since all correlations of variables shown in Table 3 were smaller than the recommended threshold of 0.7, the assumption of independence of variables is assured. Second, publication bias refers to potential bias caused by excluding studies not published due to insignificant results. The robustness of the results is indicated by a higher number of fail-safe K values (Rosenthal, 1979). The values of fail-safe k shown in Table 4 indicate the strength of the proposed hypothesis testing. Third, heterogeneity of effect sizes among the studies can be addressed by calculating I^2 value. The I^2 heterogeneity index indicates the percentage of variance in pooled studies can be attributed to the heterogeneous effect-sizes (correlation coefficients) across the studies (Higgins & Thompson, 2002). As shown in Table 4, a large amount of heterogeneity (I^2 >75%) assures high heterogeneous effect sizes across the studies of the eWOM adoption decisions model.

Table 3: Correlations Matrix for Analysis 1

Correlation	1.	2.	3.	4.	5.	6.
1. Content quality	1.00					
2. Source attribute	0.51	1.00				
3. Social endorsement	0.46	0.40	1.00			
4. Information credibility	0.52	0.59	0.48	1.00		
5. Information helpfulness	0.47	0.41	0.40	0.66	1.00	
6. eWOM adoption decisions	0.46	0.42	0.44	0.59	0.53	1.00

Table 4: Results of Hypotheses Testing for Analysis 1

Hypotheses	Study	Sample size	Main effect size estimates				Fail-Safe K	Heterogeneity tests		
			β	Lower	Upper	p-value		Q	T	I^2
H1	14	3,576	0.38^{***}	0.27	0.50	<0.001	4,499	220.77	0.24	93.50%
H2	14	3,372	0.45^{***}	0.36	0.53	<0.001	6,150	97.13	0.18	88.03%
H3	10	2,856	0.25^{***}	0.12	0.39	<0.001	2,088	82.86	0.17	88.34%
H4	12	3,195	0.27^{***}	0.14	0.41	<0.001	3,792	177.25	0.22	92.62%
H5	11	3,191	0.17^{**}	0.04	0.29	0.008	1,772	104.99	0.18	89.65%
H6	9	2,354	0.36^{***}	0.24	0.48	<0.001	2,428	118.16	0.21	92.12%
H7	4	1,513	0.34^{***}	0.16	0.51	<0.001	384	109.69	0.27	96.44%
H8	5	1,414	0.24^{***}	0.13	0.34	<0.001	512	18.32	0.11	75.19%

Notes: β, path coefficient; *** p-value < 0.001. ** p-value < 0.01. * p-value < 0.05.

4.1.2. Estimation of eWOM Adoption Decision Model

In the second stage of TSSEM, a vector of pooled correlations and its asymptotic covariance matrix can be derived from stage one. The TSSEM approach utilizes weighted least square (WLS) estimation to fit the proposed models in the stage two analysis. A structural correlation model is fitted with the WLS estimation method, and The *TSSEM2()* function is used to fit structural equation models in this stage (Cheung, 2015).

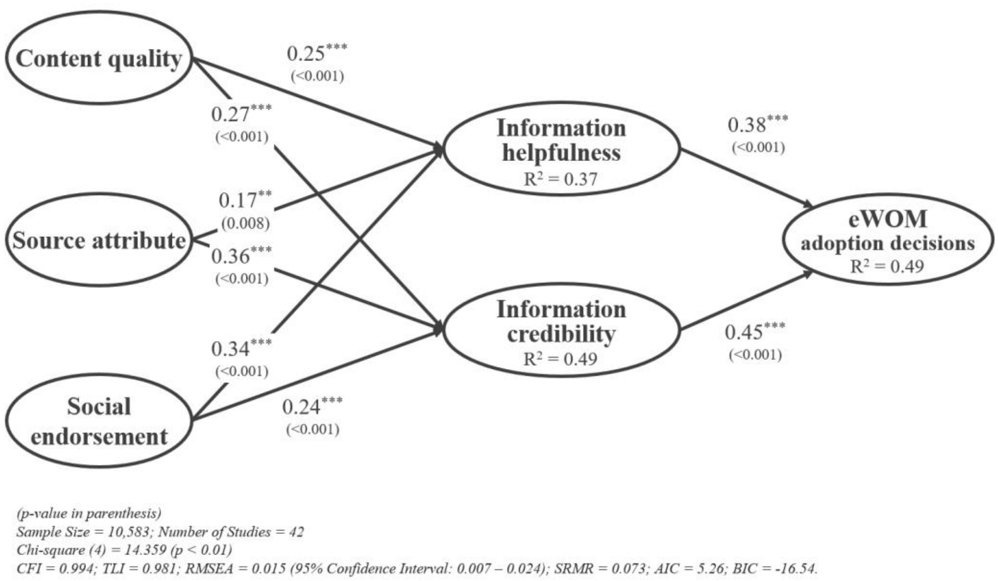

Figure 3: eWOM adoption decisions model using TSSEM

The results of the random-effects TSSEM analysis show that the proposed eWOM adoption decisions model exhibits acceptable fit to the meta-analytic data: chi-square (degrees of freedom: 4) = 14.359 (p-value < 0.001), CFI = 0.994, TLI = 0.981, SRMR = 0.073, RMSEA = 0.015 (95 percent confidence interval: 0.007-0.024). In addition, IH and IC jointly explain 49 percent of the variation of eWOM. Three antecedents explain 37 percent variance of IH and

49 percent variance of IC. Path coefficients and R-square values are shown in Figure 3, and the detailed indexes are presented in Table 4.

The findings answer our first research questions that IC is also an important antecedent of eWOM adoption decisions, along with IH (H1: 0.38, $p < 0.001$; H2: 0.45, $p < 0.001$). Furthermore, content quality, source attribute, and social endorsement significantly influence IC (H4: 0.27, $p < 0.001$; H6: 0.36, $p < 0.001$; H8: 0.24, $p < 0.001$) and IH (H3: 0.25, $p < 0.001$; H5: 0.17, $p = 0.008$; H7: 0.34, $p < 0.001$). In addition, we found no direct impact from eWOM characteristics to eWOM adoption decision (including 0.05 for content quality; -0.02 for source attribute, and 0.07 for social endorsement), which suggests that IH and IC fully mediate the impacts of eWOM characteristics on eWOM adoption decision. In addition, the results of six Sobel tests also support the notion of mediation where the p-values of six indirect relationships are all lower than 0.05. It is also noticeable that IC transfers more effect from three independent variables to eWOM (0.37, 95% CI [0.33, 0.41]) than IH does (0.20, 95% CI [0.08, 0.34]).

4.1.3. Post-hoc Analysis: Alternative Models Testing

Further, we tested an alternative model, with an additional link from IC to IH, to explore possible mediating effects of IH on the relationship between IC and eWOM adoption decisions. This was conducted with the same meta-analytic data and procedures used for the main analysis. The testing result for the alternative mode is very similar to Figure 3, except that the newly added link is not significant (IC has no significant impact on IH ($\beta = 0.22$, $p = 0.087$) and the impact of source attribute on IH became insignificant ($\beta = 0.07$, $p = 0.372$). This indicates no mediating effect of IH on the relationship between IC and eWOM adoption decisions.

4.2. Analysis 2: Compare Antecedents of IC and IH

Analysis 1 highlights the importance of IC, as well as IH, on eWOM adoption decisions. It also shows the significant impacts of three antecedents on IC and IH. However, it is also noticeable that these three antecedents affect IC and IH differently. For example, content quality has a similar impact on both variables, source attribute affect IC more than IH, and social endorsement has a stronger impact on IH than on IC. Since each of the three antecedents is a combination of several sub-dimensions, further exploring how each sub-dimension contributes to IC and IH allows us to understand what forms a better eWOM message.

Table 5: Meta-analytic Effect Sizes of eWOM Characteristics on eWOM Persuasiveness

Variable	eWOM persuasiveness	Study number	Sample size	Combined effect size	p-Value	*Q*-Value (homogeneity test)
Content quality						
• Content informativeness	IH	22	5,531	**0.572*****	<.0001	**262.01*****
	IC	7	1,894	**0.669*****	<.0001	**77.50*****
• Content strength	IH	5	1,117	**0.528*****	.0008	**18.83*****
	IC	12	2,988	**0.785*****	<.0001	**36.26*****
• Content sidedness	IH	NA				
	IC	5	1,822	**0.551*****	.0080	**232.13*****
Source attribute						
• Source credibility	IH	19	5,115	**0.506*****	<.0001	**110.88*****
	IC	13	3,611	**0.822*****	<.0001	**251.98*****
• Source attractiveness	IH	2	700			
	IC	5	1,394	**0.611*****	<.0001	**57.98*****
Social endorsement						
• Information consistency	IH	NA				
	IC	5	1,815	0.578***	<.0001	12.45
• Linear rating	IH	NA				
	IC	5	1,468	0.639***	<.0001	10.62
• Extreme rating	IH	NA				
	IC	NA				
• Information quantity	IH	5	1,802	**0.626****	.0037	**294.89*****
	IC	4	1,062	**0.503*****	<.0001	**14.30*****

To reach this goal, we conducted Analysis 2 by using bivariate meta-analysis with studies that contain primary data only. We calculated the combined effect size of each sub-dimension on two persuasiveness indexes. To manifest the result of Analysis 2, we used "metafor" (Viechtbauer, 2010) and "robumeta" (Fisher & Tipton, 2015) packages and followed the steps of Quintana (2015). First, we converted the values of Pearson's r into Fisher's z scale as the values are not normally distributed. And, based upon the values of Q-statistics, we rejected the assumption of homogeneity in the pooled studies and adopted a random-effect model to estimate the effect size of sub-dimensions.

The results are shown in Table 5. First, content strength and content informativeness generate more effect size on IC (strength: 0.785; informativeness: 0.669) than IH (strength: 0.572; informativeness: 0.528). Second, the effect of source credibility is stronger on IC ($\beta = 0.822$) than on IH ($\beta = 0.506$). Third, information quantity results in more effect size on IH ($\beta = 0.626$). Because some variables are not widely included, the comparison of effect size is ignored for these variables, including content sidedness, source attractiveness, information consistency, linear rating, and extreme rating.

4.3. Analysis 3: The Moderating Effect of Data Source on IH

To answer RQ2 - whether the magnitude of the relationships between IH and its antecedents is contingent on data source. We conducted a bivariate meta-analysis on the moderator analysis on IH in Analysis 3 and employed data source (including self-reported as primary data and crawled data as secondary data) as a moderator. We repeated the same steps in Analysis 2 (Quintana, 2015).

4.3.1. Main Effect Size Estimates of Information Helpfulness

First, we checked the heterogeneity of the pooled studies. As shown in Table 6, all the Q-values are significant, which rejects the homogeneity assumption across studies. A statistically significant Q-statistic indicates that the included studies do not share a common effect size. This also implies that the variety in effect sizes exceeds those which may be caused by sampling error (Purnawirawan et al., 2015).

For content quality, the MA results show that content informativeness, its five components, and content strength significantly impact IH. For source attribute, source credibility and its three components and source attractiveness have significant and positive effect on IH. For social endorsement, the impacts of ratings (both linear and extreme) and information quantity are all insignificant.

Table 6: Meta-analytic Effect Sizes of eWOM Characteristics on IH

Variable	Study number	Sample size	Combined effect size	p-Value	*Q*-Value (homogeneity test)
Content quality					
• Content informativeness	64	2,614,212	**0.270*****	<.0001	**18,023.03*****
0. Unidimensional (C+A+R+Ti) *	4	961	**0.609*****	<.0001	**15.08*****
1. Comprehensiveness (C)	34	2,172,325	**0.213*****	<.0001	**23,513.01*****
2. Accuracy (A)	4	2,850	**0.406****	.0016	**13.91*****
3. Relevance (R)	5	6,427	**0.541*****	.0004	**412.55*****
4. Timeliness (T)	17	431,649	**0.198*****	.0001	**4,494.70*****
• Content strength	5	1,117	**0.528*****	.0008	**18.83*****
• Content sidedness	1	570			
Source attribute					
• Source credibility	32	542,849	**0.386*****	<.0001	**8,741.20*****
0. Unidimensional (E+Tr) *	9	2,384	**0.541*****	<.0001	**61.66*****
1. Expertise (E)	13	274,861	**0.348*****	<.0001	**4,731.71*****
2. Trustworthiness (Tr)	10	265,604	**0.299*****	<.0001	**1,109.95*****
• Source attractiveness	7	108,869	**0.375*****	<.0001	**98.48*****
Social endorsement					
• Information consistency	NA				
• Linear rating	16	1,358,147	0.024	.4699	**42,208.99*****
• Extreme rating	7	485,773	0.012	.9273	**4,873.79*****
• Information quantity	9	324,938	0.310	.0652	**1,373.56*****

Note: * Unidimensional represents that this construct was measured with components listed in the parenthesis.

4.3.2. Subgroup Analysis

Next, we compared the combined effect size of three antecedents and their components based on different data sources. Table 7 reveals that data source moderates the impacts of five components (including comprehensiveness, timeliness, expertise, trustworthiness, and information quantity) on IH. Specifically, comprehensiveness, timeliness, source expertise, trustworthiness, and information quantity have a stronger effect on IH when primary data is collected and used for analysis. Interestingly, information quantity has a significant negative effect on IH when the secondary data is used as the data source, which yields a big difference of effect size (0.70) between the two sources of data.

Table 7: The Moderating Effects of Data Source.

Variable	Moderator	Study number	Sample size	Combined effect size	p-Value	*Q*-Value (homogeneity test)
Content quality						
• Content quality attribute	Primary	22	5,531	**0.572*****	<.0001	**237.90*****
	Secondary	42	2,608,681	**0.121*****	<.0001	
0. Unidimensional (C+A+R+Ti)*	Primary	4	961	**0.609*****	<.0001	
	Secondary	NA				
1. Comprehensiveness (C)	Primary	6	1,478	**0.647*****	<.0001	**99.72*****
	Secondary	28	2,170,847	**0.126*****	<.0001	
2. Accuracy (A)	Primary	3	730	**0.508*****	<.0001	
	Secondary	1	2,120			
3. Relevance (R)	Primary	4	1,001	**0.682*****	<.0001	
	Secondary	1	5,426			
4. Timeliness (Ti)	Primary	5	1,361	**0.402*****	0.001	**19.18*****
	Secondary	12	430,288	**0.119*****	0.002	
• Content strength	Primary	5	1,117	**0.528*****	0.001	
	Secondary	NA				
• Content sidedness	Primary	1	570			
	Secondary	NA				
Source attribute						
• Source credibility	Primary	19	5,115	**0.506*****	<.0001	**41.56*****
	Secondary	13	537,734	**0.229*****	<.0001	
0. Unidimensional (E+Tr)*	Primary	9	2,384	**0.541*****	<.0001	
	Secondary	NA				
1. Expertise (E)	Primary	4	1,123	**0.515*****	<.0001	**5.53***
	Secondary	9	273,738	**0.284*****	<.0001	
2. Trustworthiness (Tr)	Primary	6	1,608	**0.440*****	<.0001	**31.60*****
	Secondary	4	263,996	**0.104***	.0385	
• Source attractiveness	Primary	2	700			
	Secondary	5	108,169	**0.418*****	<.0001	
Social endorsement						
• Information consistency	Primary	NA				
	Secondary	NA				
• Linear rating	Primary	NA				
	Secondary	16	1,358,147	0.024	.4699	
• Extreme rating	Primary	NA				
	Secondary	7	485,773	0.012	.9273	
• Information quantity	Primary	5	1,802	**0.626****	.0037	**296.61*****
	Secondary	4	323,136	**-0.083*****	<.0001	

Note: * Unidimensional represents that this construct was measured with components listed in the parenthesis.

However, we cannot perform the moderating effect analysis for accuracy, relevance, and source attractiveness because MA cannot be conducted on less three studies (Kirca et al., 2005). Further, some analyses were disregarded because there is no secondary data-based study that contains content strength, and no primary data-based study contains linear rating and extreme rating. Since at least one component in the three dimensions (content quality, source attribute, and social endorsement) is supported, we claim that H9s are partially supported.

5. Discussion and Implications

5.1. Discussion of Key Findings

An increasing number of studies focus on exploring possible determinants of IC (Cheung et al., 2012; Luo et al., 2015; Luo et al., 2014) and quest its effect on the outcomes of eWOM (Bae et al., 2017; Cheung et al., 2009; Fang, 2014; Luo et al., 2013; Yan et al., 2016). To understand the importance of IC, we adopted ELM as the framework for building the nomological network and considered content quality as the central route and both source attribute and social endorsement as the peripheral route. Analysis 1 indicates that both routes are critical for decision-making and provides us a new insight into the role of IC. The significant effect of IC on the eWOM adoption decisions (H2) highlights its importance. Its insignificant effect on IH (IC->IH) further implies that it is another important antecedent of eWOM outcomes alongside IH. As we indicated, fake reviews threaten the effectiveness of online reviews and contribute to the crucial role of IC in the contemporary online environment. As a result, the adoption of a specific eWOM is highly affected by the credibility of the information.

To compare antecedents of IC and IH, from the perspective of eWOM characteristics, Analysis 1 also indicate that IC is strongly affected by source attribute, followed by content quality and social endorsement. This highlights the importance of the source credibility and source attractiveness. On the other hand, for IH, is strongly affected by social endorsement, followed by content quality and source attribute. This implies that consumers put a huge weight on the surface information cues (including the quantity of review and rating score) in an information-overloaded online environment. The surface information cues allow individuals to speed up their decision-making process. Furthermore, IH is less affected by source attribute. This result is similar to Qahri-Saremi and Montazemi (2019), who found that source-related attributes can only generate limited effects. To clarify the contributions of sub- dimensions of antecedents to IC and IH, Analysis 2 provides several observations. First, source attribute has a stronger impact on IC than on IH. This is reasonable since both of them focus on credibility. Second, social endorsement has a stronger impact on IH than on IC. This is especially true when quantity (one component) is the spot. This echoes the above discussion that information overload shifts customers' focus to some surface information. Content quality has a similar influence on IC and IH. To increase the quality of a message, review writers should focus on building statements with a compelling claim and strong data (Kim & Benbasat, 2006).

The moderating effect of data source on the relationships between IH and its antecedents further illustrates some interesting results (Analysis 3). First, comparing the effect sizes of primary studies, we found similar effect when using different operationalization on content quality (i.e., content informativeness and content strength). The results also show that the influence of relevance and comprehensiveness on IH is more important than accuracy and timeliness. In other words, consumers would like to obtain an appropriate and broad range of information that can be used for decision-making. For source attribute, when consumers face information overload, they may process information using the peripheral cues and using the information about the source to infer trust. It is more convenient and efficient. Second, comparing the effect sizes of secondary studies, source attractiveness and source expertise have more impact on IH. It means the platform should provide more information of reviewer for people to evaluate, such as the duration of membership, the number of reviews, the credential, the social structural information, etc. Third, as we expected, studies with primary data generate a larger effect size. The effect size difference is bigger (> 0.5) for some antecedents (including comprehensiveness and information quantity) and smaller (< 0.5) for some antecedents (including content informativeness, timeliness, source credibility, expertise, and trustworthiness). Since crawling data from platforms is getting popular in academic research, researchers should expect a relatively small effect size (< 0.2) and possible insignificant links when this approach is adopted. For example, linear rating and extreme rating have no significant effects on IH. Furthermore, for information quantity, a positive (negative) impact was found when primary (secondary) data is used. This implies that research subjects consider the quantity of information is important in a simplified condition (such as lab experiment). However, the information overload or fake review problems cause actors to downgrade the helpfulness of a specific eWOM message. The negative relationship between volume and information helpfulness is consistent with (Wang et al., 2019).

5.2. Limitations

Even though the above results are interesting and worth noticing, careful attention is still needed before further interpreting or applying the results of this study. The following includes some significant limitations of this study. First, to answer RQ1, we included only studies with primary data because IC was measured with a self-report approach. Second, to answer RQ2, because the number of studies with secondary data is insufficient, we skipped the moderator analysis for the sub-dimensions of content quality, including accuracy and relevance. On the other hand, because the number of studies with primary data is insufficient, we skipped the moderating effect analysis for the one sub-dimension of source attribute (source attractiveness) and two sub-dimensions of social endorsement (information linear rating and information extreme rating). Third, we included 42 studies related to eWOM adoption decisions for MASEM and 38 for bivariate meta-analysis to answer RQ1. We include 37 published articles related to IH for bivariate meta-analysis to answer RQ2. Even though the research was thoroughly designed and carefully conducted to include all possible relevant articles in IS journals and conferences, it is still possible that some studies are omitted because of any possible negligence.

5.3. Implications

Our research work is motivated by two critical issues in recent eWOM research and MA. First, even though IC is getting its importance, past MA studies only focused on IH. Whether information adoption decision is also a function of IC hasn't been explored systematically. Second, utilizing secondary data for model testing is getting popular in eWOM research. Whether the magnitude of the impact of eWOM characteristics on IH is contingent on data source hasn't been explored as well. After collecting sixty-eight eWOM papers, we first demonstrated the importance of IC with MASEM and bivariate meta-analysis. In addition, we also illustrated that the strength of the relationships between IH and some of its antecedents is contingent on the source data.

5.3.1. Theoretical Implications

This study contributes to related research in the following ways. First, we highlighted the important role of IC in eWOM. Since early studies mainly consider IH as the only antecedent of information adoption, past MA, therefore, focused on exploring the moderators of the relationships between IH and its antecedents. In this paper, we argued the importance of IC in the context filled with fake reviews and online comments that may be manipulated by the manufacturers. Furthermore, we provided evidence to support our argument based on the data collected by past related studies with the MASEM approach. Interestingly, we found that the importance of IC on eWOM adoption decisions is higher than IH - the most studied antecedent. Even though such a result may be caused by most studies that contain IC adopts a self-report survey approach, IC still has a significant and positive impact on adoption decisions. Furthermore, through the bivariate approach, we also showed that the combined effect size of several antecedents (eWOM characteristics) is stronger for IC. This implies that future eWOM studies should not neglect IC in building a research model to understand how consumers react to online comments or reviews.

Second, we illustrated how the magnitude of the relationships between IH and its antecedents is contingent on the source of data. Our results show that the coefficients are much larger when primary data is adopted. While the impact of common method bias cannot be totally ruled out, a self-report survey is still preferred in some conditions. Primary data still have certain advantages because the adopted measurement is dedicated to the focal constructs. As an outcome, the found coefficients are much more substantial. However, even though the coefficients obtained with secondary data are much smaller, accessing such data is relatively easier and with lower cost. Therefore, future research is encouraged to adopt the most appropriate approach based on the purpose of the study. For example, primary data is preferred when picking a proxy variable to fully represent the focal construct is not likely. However, researchers may take advantage of each approach and design a comprehensive study with data from both sources.

5.3.2. Practical Implications

This study also generates several implications to managers of review sites, online forums, vendor platforms, and social media. First, we suggest practitioners to provide incentives (e.g., reward points) to encourage reviewers to share high-quality content since user generated content is more persuasive than marketer generated content. To ease the burden for those reviewers who cannot express their opinions in a subjective form platform owners may fix the format of the content and outline the information that should be included for a good review.

Second, we suggest that practitioners should effectively utilize "tag" to similar functions to facilitate eWOM adoption decisions. We suggest practitioners to provide explicit information to indicate the credibility of eWOM (i.e., Amazon "verified purchase", TripAdvisor "date-of-stay", and Yelp "check-in"). This mechanism is similar to the widely adopted tag which shows the helpfulness of a message (i.e., helpful votes). In the same way, this idea also applies to the source of eWOM. For example, Yelp "Elite", Amazon "Top Contributor", Tripadvisor "Contributions", and Google "Local Guide-Level" are the credentials to illustrate the credibility of reviewers. Another example is "Review Highlight" which is provided by Yelp to show the extent to which actual arguments are consistent with other reviewers.

Third, we suggest practitioners to adopt artificial intelligence (AI) techniques to deal with information overload and fake news issues. AI-empowered robots can detect the effectiveness of reviews (based on the length, readability, accuracy, and relevance) and determine the plausibility of the arguments embedded (e.g., claim, data, and backing). Robots can also highlight/summarize the pros and cons mentioned in the review to reduce cognitive efforts. Moreover, AI-empowered robots can detect whether the eWOM written by the reviewers is appropriate and relevant. Those irrelevant and inaccurate reviews can then be hid, downgraded, or moved to other pages to ease cognitive loading.

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Appendix A: Studies Included in the Meta-analysis

Paper ID	Author	Year	Title	Publication	Analysis 1	Analysis 2	Analysis 3
[01]	Cheung, C. M., Lee, M. K., & Rabjohn, N.	2008	The impact of electronic word-of-mouth: The adoption of online opinions in online customer communities	Internet Research	✓	✓	✓
[02]	Forman, C., Ghose, A., & Wiesenfeld, B.	2008	Examining the relationship between reviews and sales: The role of reviewer identity disclosure in electronic markets	Information Systems Research			✓
[03]*	Watts, S. A., & Zhang, W.	2008	Capitalizing on content: Information adoption in two online communities	Journal of the Association for Information Systems	✓		
[04]	Cheung, M. Y., Luo, C., Sia, C. L., & Chen, H.	2009	Credibility of electronic word-of-mouth: Informational and normative determinants of on-line consumer recommendations	International Journal of Electronic Commerce	✓	✓	
[05]	Jin, X. L., Cheung, C. M., Lee, M. K., & Chen, H. P.	2009	How to keep members using the information in a computer-supported social network.	Computers in Human Behavior		✓	✓
[06]	Zhang, K. Z., Lee, M. K., & Zhao, S. J.	2010	Understanding the Informational Social Influence of Online Review Platforms	ICIS	✓		
[07]	Cheung, C. M. Y., Sia, C. L., & Kuan, K. K.	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		✓	
[08]	Korfiatis, N., GarcíA-Bariocanal, E., & 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			✓
[09]	Xu, P., Chen, L., Wu, L., & Santhanam, R.	2012	Visual Presentation Modes in Online Product Reviews and Their Effects on Consumer Responses	AMCIS	✓		
[10]	Yin, D., Mitra, S., & Zhang, H.	2012	Mechanisms of negativity bias: an empirical exploration of App reviews in Apple's App store	ICIS			✓
[11]	Chong, A. Y. L., & Ngai, E. W.	2013	What influences travellers' adoption of a location-based social media service for their travel planning?	PACIS	✓		
[12]*	Fan, H., Lederman, R.,	2013	How online health forum users assess user-generated	ECIS		✓	

Paper ID	Author	Year	Title	Publication	Analysis 1	Analysis 2	Analysis 3
	Smith, S., & Chang, S.		content: Mixed-method research				
[13]	Hsu, C. L., Lin, J. C. C., & Chiang, H. S.	2013	The effects of blogger recommendations on customers' online shopping intentions	Internet Research	✓	✓	✓
[14]	Jensen, M. L., Averbeck, J. M., Zhang, Z., & Wright, K. B.	2013	Credibility of anonymous online product reviews: A language expectancy perspective	Journal of Management Information Systems	✓		
[15]	Li, M., Huang, L., Tan, C. H., & Wei, K. K.	2013	Helpfulness of online product reviews as seen by consumers: Source and content features.	International Journal of Electronic Commerce		✓	✓
[16]	Luo, C., Luo, X. R., Schatzberg, L., & Sia, C. L.	2013	Impact of informational factors on online recommendation credibility: The moderating role of source credibility.	Decision Support Systems	✓	✓	
[17]	Fang, Y. H.	2014	Beyond the credibility of electronic word of mouth: Exploring eWOM adoption on social networking sites from affective and curiosity perspectives	International Journal of Electronic Commerce	✓	✓	
[18]	Furner, C. P., Zinko, R. A., Zhu, Z., McDowell, W. C., & Dalton, A.	2014	Online Word-Of-Mouth and Mobile Product Reviews: An Experimental Investigation of the Mediating Role of Mobile Self Efficacy	WHICEB	✓	✓	
[19]	Huang, L. T., & Kuo, F. J.	2014	A Study on Travel Information Adoption Intention in the Online Social Community: The Perspectives of Customer Experience and Information Adoption Model	PACIS	✓	✓	
[20]	Luo, C., Wang, Y., Wu, N., Liang, X., & Guo, Y.	2014	The Influence of eWOM and Editor Information on Information Usefulness in Virtual Community	PACIS		✓	✓
[21]	Luo, C., Wentian, L., Fu, X., Zeng, T., & Lan, Y.	2014	Managing Uncertainty on eWOM: a Comparison Study between Commercial and Third Party Websites	PACIS	✓		
[22]	Luo, C., Wu, J., Shi, Y., & Xu, Y.	2014	The effects of individualism–collectivism cultural orientation on eWOM information	International Journal of Information Management		✓	
[23]	Peng, C. H., Yin, D., Wei, C. P., & Zhang, H.	2014	How and when review length and emotional intensity influence review helpfulness: Empirical evidence from Epinions	ICIS			✓

Paper ID	Author	Year	Title	Publication	Analysis 1	Analysis 2	Analysis 3
[24]	Shen, X. L., Zhang, K. Z., & Zhao, S. J.	2014	Understanding information adoption in online review communities: the role of herd factors	HICSS	✓		
[25]	Stuart, D., Teng, S., Khong, K. W., Goh, W. W., & Chong, A. Y. L.	2014	Examining the antecedents of persuasive eWOM messages in social media.	Online Information Review	✓		
[26]	Yin, D., Bond, S. D., & Zhang, H.	2014	Anxious or angry? Effects of discrete emotions on the perceived helpfulness of online reviews	MIS Quarterly			✓
[27]	Yin, G., Wei, L., Xu, W., & Chen, M.	2014	Exploring Heuristic cues for Consumer Perceptions of Online Reviews Helpfulness: The Case of Yelp. Com	PACIS			✓
[28]	Zhang, K. Z., Zhao, S. J., Cheung, C. M., & Lee, M. K.	2014	Examining the influence of online reviews on consumers' decision-making: A heuristic–systematic model	Decision Support Systems	✓		
[29]	Zhu, L., Yin, G., & He, W.	2014	Is this opinion leader's review useful? Peripheral cues for online review helpfulness	Journal of Electronic Commerce Research			✓
[30]	Kuan, K. K., Hui, K. L., Prasarnphanich, P., & 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			✓
[31]	Luo, C., Luo, X. R., Xu, Y., Warkentin, M., & Sia, C. L.	2015	Examining the moderating role of sense of membership in online review evaluations	Information & Management		✓	
[32]	Shih, H. P., Lai, K. H., & Cheng, T. C. E.	2015	A Dual-Process Model to Assess User Attitudes and the Likelihood of Electronic Word-Of-Mouth Adoption	PACIS	✓		
[33]	Xu, P., Chen, L., & Santhanam, R.	2015	Will video be the next generation of e-commerce product reviews? Presentation format and the role of product type	Decision Support Systems	✓		
[34]	Xu, X., & Yao, Z.	2015	Understanding the role of argument quality in the adoption of online reviews	Online Information Review	✓	✓	✓
[35]	Aghakhani, N., Kalantar, H., & Salehan, M.	2016	Adoption of Implicit eWOM in Facebook: An Affect-as-Information Theory Perspective	AMCIS	✓		
[36]	Dai, Y., & Jiang, Y.	2016	The Research of Online Reviews' Influence towards management response on Consumer Purchasing Decisions	WHICEB	✓		

Paper ID	Author	Year	Title	Publication	Analysis 1	Analysis 2	Analysis 3
[37]	Jing, L., Xin, X., & Ngai, E	2016	An examination of the joint impacts of review content and reviewer characteristics on review usefulness-the case of Yelp.com	ICIS			✓
[38]	Matute, J., Polo-Redondo, Y., & Utrillas, A.	2016	The influence of EWOM characteristics on online repurchase intention	Online Information Review		✓	
[39]*	Tang, J., Sun, Y., Yang, S., & Sun, Y.	2016	Revisit the information adoption model by exploring the moderating role of tie strength: a perspective from construal level theory	PACIS	✓	✓	✓
[40]*	Yan, Q., Wu, S., Wang, L., Wu, P., Chen, H., & Wei, G.	2016	E-WOM from e-commerce websites and social media: Which will consumers adopt?	Electronic Commerce Research and Applications		✓	✓
[41]	Yin, D., Mitra, S., & 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			✓
[42]	Aghakhani, N., Oh, O., & Gregg, D.	2017	Beyond the Review Sentiment: The Effect of Review Accuracy and Review Consistency on Review Usefulness	ICIS			✓
[43]	Bae, S. J., Lee, H., Suh, E. K., & Suh, K. S.	2017	Shared experience in pretrip and experience sharing in posttrip: A survey of Airbnb users	Information & Management	✓	✓	✓
[44]	Guo, B., & Zhou, S.	2017	What makes population perception of review helpfulness: an information processing perspective	Electronic Commerce Research			✓
[45]	Peng, C. H., Wei, C. P., Yin, D., & Zhang, H.	2017	Impact of perspective taking on reviewer behavior: A multi-method exploration. In 38th International Conference on Information Systems	ICIS			✓
[46]*	Teng, S., Khong, K. W., Chong, A. Y. L., & Lin, B.	2017	Persuasive electronic word-of-mouth messages in social media	Journal of Computer Information Systems	✓		
[47]	Vijay, T. S., Prashar, S., Parsad, C., & Kumar, M.	2017	An Empirical Examination of the Influence of Information and Source Characteristics on Consumers' Adoption of Online Reviews	PACIS	✓	✓	✓
[48]	Aghakhani, N., Karimi, J., & Salehan, M.	2018	A unified model for the adoption of electronic word of mouth on social network	International Journal of Electronic Commerce	✓		

Paper ID	Author	Year	Title	Publication	Analysis 1	Analysis 2	Analysis 3
			sites: Facebook as the exemplar				
[49]	Cao, C., Yan, J., & Li, M.	2018	Understanding the Determinants of Online Consumer Review Helpfulness in Social Networking Service Context	PACIS		✓	✓
[50]	Chong, A. Y. L., Khong, K. W., Ma, T., McCabe, S., & Wang, Y.	2018	Analyzing key influences of tourists' acceptance of online reviews in travel decisions	Internet Research	✓	✓	✓
[51]	Coursaris, C. K., Van Osch, W., & Albini, A.	2018	Antecedents and consequents of information usefulness in user-generated online reviews: A multi-group moderation analysis of review valence	AIS Transactions on Human-Computer Interaction	✓	✓	✓
[52]*	Filieri, R., Hofacker, C. F., & Alguezaui, S.	2018	What makes information in online consumer reviews diagnostic over time? The role of review relevancy, factuality, currency, source credibility and ranking score	Computers in Human Behavior		✓	✓
[53]	Filieri, R., McLeay, F., Tsui, B., & Lin, Z.	2018	Consumer perceptions of information helpfulness and determinants of purchase intention in online consumer reviews of services	Information & Management	✓	✓	✓
[54]	Lei, Z., Yin, D., & Zhang, H.	2018	I or You: Whom Should Online Reviewers Direct Their Attention To, and When?	ICIS			✓
[55]	Luo, C., Luo, X. R., & Bose, R.	2018	Information usefulness in online third party forums	Computers in Human Behavior		✓	✓
[56]	Siering, M., Muntermann, J., & Rajagopalan, B.	2018	Explaining and predicting online review helpfulness: The role of content and reviewer-related signals	Decision Support Systems			✓
[57]	Wang, F., & Karimi, S.	2018	Linguistic Style and Online Review Helpfulness	ICIS			✓
[58]*	Yin, C., Sun, Y., Fang, Y., & Lim, K.	2018	Exploring the dual-role of cognitive heuristics and the moderating effect of gender in microblog information credibility evaluation	Information Technology & People		✓	
[59]	Cho, V., & Chan, D.	2019	How social influence through information adoption from online review sites affects collective decision making	Enterprise Information Systems	✓		
[60]	Cui, L., Jiang, H., Deng, H., & Zhang, T.	2019	The influence of the diffusion of food safety information through social media on consumers' purchase intentions	Data Technologies and Applications	✓	✓	

Paper ID	Author	Year	Title	Publication	Analysis 1	Analysis 2	Analysis 3
[61]	De Keyzer, F., Dens, N., & De Pelsmacker, P.	2019	The impact of relational characteristics on consumer responses to word of mouth on social networking sites	International Journal of Electronic Commerce	✓		
[62]	Lee, J., & Hong, I. B.	2019	Consumer's electronic word-of-mouth adoption: the trust transfer perspective	International Journal of Electronic Commerce	✓	✓	✓
[63]	Shihab, M. R., & Putri, A. P.	2019	Negative online reviews of popular products: understanding the effects of review proportion and quality on consumers' attitude and intention to buy	Electronic Commerce Research	✓		
[64]*	Tan, W. K., & Lee, B. Y.	2019	Investigation of electronic-word-of-mouth on online social networking sites written by authors with commercial interest	Online Information Review	✓	✓	
[65]	Thomas, M. J., Wirtz, B. W., & Weyerer, J. C.	2019	Determinants of Online Review Credibility and Its Impact on Consumers' Purchase Intention	Journal of Electronic Commerce Research	✓	✓	
[66]	Xiao, L., & Li, Y.	2019	Examining the Effect of Positive Online Reviews on Consumers' Decision Making: The Valence Framework	Journal of Global Information Management	✓	✓	✓
[67]	Wang, P., Li, H., & Liu, Y.	2020	Disentangling the factors driving electronic word-of-mouth use through a configurational approach	Internet Research	✓		
[68]	Yang, S., Yao, J., & Qazi, A.	2020	Does the review deserve more helpfulness when its title resembles the content? Locating helpful reviews by text mining	Information Processing & Management			✓

Note: Papers marked by "*" have provided two separate, independent studies