The effect of electronic word-of-mouth on sales

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The increasing amount of electronic word of mouth (eWOM) has significantly affected the way consumers make purchase decisions. Empirical studies have established an effect of eWOM on sales but disagree on which online platforms, products, and eWOM metrics moderate this effect. The authors conduct a meta-analysis of 1,532 effect sizes across 96 studies covering 40 platforms and 26 product categories. On average, eWOM is positively correlated with sales (.091), but its effectiveness differs across platform, product, and metric factors. For example, the effectiveness of eWOM on social media platforms is stronger when eWOM receivers can assess their own similarity to eWOM senders, whereas these homophily details do not influence the effectiveness of eWOM for e-commerce platforms. In addition, whereas eWOM has a stronger effect on sales for tangible goods new to the market, the product life cycle does not moderate the eWOM effectiveness for services. With respect to the eWOM metrics, eWOM volume has a stronger impact on sales than eWOM valence. In addition, negative eWOM does not always jeopardize sales, but high variability does.

Keywords: electronic word of mouth, online platforms, social media, eWOM metrics, meta-analysis

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The Effect of Electronic Word of Mouth on Sales: A Meta-Analytic Review of Platform, Product, and Metric Factors

In marketing, word of mouth (WOM) is the act of consumers providing information about goods, services, brands, or companies to other consumers. Such information communicated through the Internet (through, e.g., reviews, tweets, blog posts, "likes," "pins," images, video testimonials) is called "electronic word of mouth" (eWOM), and it represents one of the most significant developments in contemporary consumer behavior. With more than three billion consumers and seven billion devices connected to the Internet (International Telecommunication Union 2014), eWOM has become ubiquitous and accessible, turning consumers into "web-fortified" decision makers (Blackshaw and Nazzaro 2006). Inducing, collecting, and displaying eWOM have become priorities of many companies as part of their efforts to stimulate sales. According to Bain & Company (Barry et al. 2011), the average billion-dollar company spends $750,000 a year on earned media, with some early adopters such as Dell and American Express investing significantly more. Although the market relevance of eWOM is recognized, many professionals have not yet determined how to manage eWOM successfully. A Forrester survey (Elliott et al. 2012) of interactive marketers shows that assessing the return on investment of eWOM-related efforts is considered one of the greatest challenges interactive marketers face today.

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The topic of assessing eWOM's impact on firm performance has also garnered a great amount of academic interest. In the past 15 years, more than 100 studies have investigated whether and to what extent eWOM is linked to the bottom line. Yet the number of studies addressing the effectiveness of eWOM has decreased in recent years (for an overview of the studies and effect sizes from 1999 to 2013, see the Web Appendix), suggesting that a full understanding of the phenomenon has been reached; nonetheless, two key debates remain unsettled (see Table 1). The first inconclusive area of investigation pertains to the moderating role of platform and product characteristics on the effect of eWOM on sales. Prior studies have mostly relied on a single sample (and, consequently, *one* platform and/or *one* product type) and thus have not been able to investigate the moderating effects of these factors. As Forman, Ghose, and Wiesenfeld (2008, p. 291) note, "[The] research in this arena is fragmented [and] we have yet to understand why, how, and what aspects of online consumer-generated product reviews influence sales."

The second inconclusive area involves eWOM metrics. Although most research has concluded that eWOM has a significant monetary effect on sales beyond other marketing-mix effects (Chen, Wang, and Xie 2011; Chevalier and Mayzlin 2006; Moe and Trusov 2011), there is disagreement about which particular metrics of eWOM representing different aspects (e.g., reach, preference, consumer [dis]agreement) drive the effect.[1] Whereas some researchers find evidence that the number of online reviews predicts product sales (e.g., Duan, Gu, and Whinston 2008; Gu, Park, and Konana 2012; Ho-Dac, Carson, and Moore 2014; Liu 2006; Xiong and Bharadwaj 2014), others posit that the main predictor is not the volume of eWOM, but rather its valence (e.g., Chintagunta, Gopinath, and Venkataraman 2010; Dellarocas, Zhang, and Awad 2007), variance (e.g., Sun 2012), mere existence (e.g., Davis and Khazanchi 2008), or specific content (e.g., Onishi and Manchanda 2012). In addition, findings on the impact of negative eWOM are inconclusive. Some studies have shown that negative eWOM is detrimental and even more powerful in decreasing sales than positive eWOM is in increasing it (Chevalier and Mayzlin 2006; Sun 2012); conversely, other studies have shown that the presence of negative eWOM increases product evaluations and sales (e.g., Doh and Hwang 2009; Hiura et al. 2010; Kikumori and Ono 2013).

These varying results hinder the development of systematic insight that can help marketers make informed decisions about eWOM management. The current study discusses a meta-analysis that offers a comprehensive synthesis across studies. This is important for two reasons. First, the studies differ substantively in terms of online platform, industry, product, geographic region, and eWOM metrics investigated. Second, the studies differ in methodological approaches. Meta-analytic methods enable researchers to (1) obtain empirical generalizations about a specific effect size across varying substantive and methodological conditions and (2) examine whether and how these conditions affect the focal effect size (see Farley, Lehmann, and Sawyer 1995). Therefore, our meta-analysis contributes to understanding of the influence of platform characteristics, product characteristics, and eWOM metrics on the effect of eWOM on sales.

First insights along these lines come from the work of Floyd et al. (2014) and You, Vadakkepatt, and Joshi (2015). Floyd et al. (2014) examine 26 studies investigating the effect of online reviews on firm performance. Although consumer-generated online reviews are an important category of eWOM, the phenomenon of eWOM cannot be reduced to online reviews *only*. You, Vadakkepatt, and Joshi's (2015) meta-analysis focuses on the effects of consumer-generated information on firm performance, extending the analysis to 51 papers and a few online platforms (i.e., blogs, discussion forums, and Twitter). Although these two studies provide important insights into the impact of eWOM on sales, their generalizations are limited in terms of the number of platforms, products, and metrics investigated, leaving the aforementioned debates unresolved. Our study provides answers to these debates. We outline the main differences between our study and previous meta-analyses in Table 2 and the Web Appendix.

This study makes several contributions to the literature on eWOM and interpersonal influence. First, we offer further insight into the moderating effects of platform and product characteristics (across 40 platforms and 26 product categories). To do so, we compile a unique data set by collecting supplementary time-varying information that reflects the nature of each platform and product category at the time of the original data collection. This is critical in meta-analytic work because it is often impossible to retrieve time-specific information that matches the primary studies. Using the Wayback Machine (https://archive.org/web), an Internet archive that provides access to past platform interfaces, we tracked the evolution of each platform over time and the type of information provided about the eWOM senders and messages. Moreover, we employed expert coders to code additional product characteristics at the time of the original data collection. With the addition of this primary data set, we could investigate dimensions of eWOM that were not part of the primary studies and that have been neglected as possible moderators of the effect of eWOM on sales. Thus, our meta-analysis moves beyond a summary of extant literature. Our empirical results reveal how both platform and product characteristics influence the effect of eWOM on sales. Among other things, we find that the effectiveness of eWOM on social media platforms is stronger for platforms that enable eWOM receivers to assess their own similarity to eWOM senders on the basis of username, avatar, profile page, and geographic location. However, for e-commerce platforms, these homophily details do not influence the effectiveness of eWOM. Instead, we find that on e-commerce platforms, eWOM increases sales more when it is immediately visible (i.e., no scrolling is required to access eWOM information) and when it is less structured (e.g., no summaries are provided). We also find that different moderators influence eWOM effectiveness across products. For example, eWOM has a stronger effect on sales for tangible goods new to the market. In contrast, the product life cycle does not moderate the eWOM effectiveness for services and hedonic products.

Second, we examine the interplay between platform- and product-level moderators of eWOM effectiveness to

[1]In the remainder of the article, we use the term "eWOM metrics" (e.g., "valence"). We acknowledge that it is the underlying aspects of eWOM (e.g., "preference") that drive sales and not the metrics per se.

Table 1
CONCEPTUAL FRAMEWORK TO ADDRESS UNSETTLED DEBATES

	RQ$_1$: For Which Platform and Product Characteristics Is eWOM More Effective?		*RQ$_2$: Which eWOM Metric Is More Effective?*
	Platforms	*Products*	
Unsettled debate	Insufficient evidence due to single-platform studies	Insufficient evidence due to single-product category studies	• Volume increases sales more than valence (e.g., Liu 2006) • Volume increases sales less than valence (e.g., Chintagunta et al. 2010) • Negative eWOM decreases sales (e.g., Chevalier and Mayzlin 2006) • Negative eWOM increases sales (e.g., Doh and Hwang 2009) • Unclear effect of variance (e.g., Sun 2012)
Key characteristics	• Platform type - Social media platform - Review platform - E-commerce platform - Other • eWOM sender - Homophily - Trustworthiness • eWOM message - Time stamp - Helpfulness rating - Visibility - Structured display • Platform maturity • eWOM posting costs • Product characteristics • Operationalization of eWOM metrics	• Functional risk - Tangible vs. digital vs. service - Hedonic vs. utilitarian product - New vs. mature product • Financial risk - High vs. low risk • Platform characteristics • Operationalization of eWOM metrics	• Operationalization of eWOM metrics - eWOM volume - eWOM valence - eWOM composite valence–volume - eWOM variance • Platform characteristics • Product characteristics
Methodological approach	• Coding of time-varying information about 40 platforms at the time of the original data collection • Overall assessment of the relative importance of different platform types and characteristics (weighted random-effect HiLMA) • Platform-specific analysis of moderating effects (weighted random-effect split-sample HiLMA)	• Coding of time-varying information about 26 product categories at the time of the original data collection • Overall assessment of the relative importance of different product types and characteristics (weighted random-effect HiLMA) • Product-specific analysis of moderating effects (weighted random-effect split-sample HiLMA)	• Inclusion of metrics other than volume and valence (e.g., variance; 12 submetrics in total) • Differentiation between the absolute and relative effect of valence: introduction of a new metric (composite valence–volume) • Overall assessment of the relative importance of the most common metrics (weighted random-effect HiLMA) • Metric-specific analysis of moderating effects (weighted random-effect split-sample HiLMA)

identify not only for which platform and product characteristics but also for which platform–product combinations eWOM more effectively increases sales. For example, when a product is new to the market, eWOM is more effective when appearing on an e-commerce platform or a review platform rather than on a social media platform.

Third, we investigate other representations of eWOM (e.g., variance) important in the marketplace, whose effects on sales remain unclear. Thus, we go beyond analyzing volume and valence metrics to investigate the differential effects of four key metrics of eWOM (i.e., volume, valence, composite valence–volume, and variance) comprising 12 submetrics categorized on the basis of their operationalizations. By considering this larger set of metrics, we capture variation within all metrics (e.g., how the effect of positive valence differs from the effect of average valence and positive volume), thereby gaining more detailed insight in the mechanisms underlying the impact of eWOM on sales. Importantly, we show that failing to distinguish between the submetrics of eWOM may lead to a misinterpretation of the relative effect of volume versus valence. In particular, we introduce a new variable, composite valence–volume (e.g., total number of five-star ratings), which has been commonly labeled as valence (e.g., percentage of five-star ratings). We argue that these two metrics are conceptually different in that they represent different underlying aspects, and we show that using a more precise measure of valence—uncontaminated by volume—reverses the conclusion that valence has a stronger effect on sales than volume, as previous meta-analyses have shown. We find this result consistently across platforms and products, with the exception of services, for which the effect of volume metrics on sales is not significantly different from the effect of positive valence.

Table 2
KEY DIFFERENCES ACROSS META-ANALYSES ON eWOM

	Sample				*Focus*		
Study	*Number of Studies*	*Number of Effects*	*Number of Platforms*	*Number of Product Categories*	*Metrics*	*Platform Characteristics*	*Product Characteristics*
Floyd et al. (2014)	26	443	16	13	Volume Valence		Product involvement
You, Vadakkepatt, and Joshi (2015)	51	339 (volume) 271 (valence)	15	18	Volume Valence	Independent review sites, specialized review sites, community-based sites	Privately consumed, trialability, category competition, durables
This study	96	1,532 589 (volume) 596 (valence) 108 (composite valence–volume) 137 (variance) 102 (other)	40	26	Volume Valence Composite valence–volume Variance Other	Social media platforms, review platforms, e-commerce platforms, other platforms, eWOM sender homophily, eWOM sender trustworthiness, eWOM message time stamp and helpfulness rating, eWOM visibility, eWOM structured display, platform maturity, eWOM posting costs	Tangible, digital, service, utilitarian, hedonic, financial risk, new, mature

Fourth, to better monitor and manage eWOM, it is crucial to understand not only which eWOM metric contributes more to a sales increase (e.g., volume vs. valence) but also which metric can significantly decrease sales. We are the first to reconcile evidence of the effects of negative eWOM on sales by identifying platform and product characteristics for which negative eWOM (negative valence and negative volume) does not jeopardize sales and those for which it does. Furthermore, we show that another submetric that is often overlooked—variability (consumer disagreement about product quality)—decreases sales on e-commerce platforms and for tangible, utilitarian, new, and high-financial-risk products.

In the following sections, we first discuss our conceptual framework and then describe the collection and coding of 1,532 effect sizes from 96 studies across 40 platforms and 26 product categories. We present results from two meta-analytic procedures—namely, a Hedges–Olkin meta-analysis (HOMA; Hedges and Olkin 1985) and a hierarchical linear meta-analysis (HiLMA; Lipsey and Wilson 2001). Using split samples, we also show how the moderators of the link between eWOM and sales differ across platforms, products, and metrics. Finally, we discuss the implications of our findings for marketers and researchers and provide directions for further research.

CONCEPTUAL FRAMEWORK

As the market environment has become more saturated with products and marketer-generated information, it has become increasingly difficult for consumers to know and process all alternatives. Electronic word of mouth helps consumers minimize uncertainty (Dichter 1966; Roselius 1971), and thus further insights into the specific circumstances in which eWOM is a more powerful risk-reducing tool are required. In the following sections, we provide a framework that describes the key characteristics of the platforms, products, and eWOM metrics that may moderate the impact of eWOM on sales (see Table 1).

For Which Platform and Product Characteristics Is eWOM More Effective?

Platform characteristics. It is important to account for the characteristics of the channel in which eWOM is displayed (Berger and Iyengar 2013; Schweidel and Moe 2014). We examine five characteristics of the eWOM platform. First, we account for the different types of platforms: (1) social media platforms (e.g., Facebook, blogs, discussion forums), (2) review platforms (e.g., Epinions, Yahoo!Movies), (3) e-commerce platforms (e.g., Amazon.com, eBay), and (4) other platforms (e.g., Internet overall). Second, we acknowledge that consumers often evaluate the value of online platforms as information channels on the basis of additional information provided about the eWOM sender. Of particular importance are signals of homophily and trustworthiness (Fogg et al. 2003; Hung, Li, and Tse 2011). Prior research has shown that messages coming from similar others are more persuasive (Brown and Reingen 1987; Forman, Ghose, and Wiesenfeld 2008; Reichelt, Sievert, and Jacob 2014). Electronic word of mouth is also more effective when receivers trust the sender and can be confident about their good intentions (McGinnies and Ward 1980). Consequently, information about the sender aids receivers in assessing whether the eWOM is relevant to them and whether the sender is trustworthy, potentially leading to a higher correlation with sales. Third, extant studies have shown that additional information provided about the eWOM message, such as time stamp and helpfulness rating, increases sales (Berger 2014; Robins, Holmes, and Stansbury 2010). Similarly, when eWOM information is immediately visible and displayed in a more structured way (e.g., with summaries of the most representative positive and negative reviews), it may have a greater impact on the bottom line. Fourth, the reputation of a platform as a valuable information channel needs time to develop. In earlier stages of development, platforms attract fewer visitors, and they experience smaller network effects than more mature platforms. Therefore, eWOM displayed on platforms introduced more recently may have a lesser impact on sales than eWOM appearing on more mature platforms. Fifth, we differentiate platforms according to posting policies. Specifically, eWOM senders may incur posting hurdles. For example, they may need to have purchased the product or registered as a member to create or disseminate a review, upload a video, and so on (Mayzlin, Dover, and Chevalier 2014). Previous research has shown that such costs decrease the prevalence of fake reviews and thus increase the value of eWOM (Ott, Cardie, and Hancock 2012). Therefore, the effect of eWOM on sales may be greater for platforms imposing eWOM posting costs.

Product characteristics. The topic of eWOM pertains to goods, services, brands, and companies. These goods and services have different levels of functional and financial risk (Wangenheim and Bayón 2004). To reduce uncertainty about perceived risk, consumers consult with others (Roselius 1971). We examine four product characteristics moderating eWOM effectiveness, for which the expected differences depend on the importance of functional and financial risks.

Functional risk is linked to uncertainty about a product's performance, and research has demonstrated that it is higher for services (vs. tangible goods), hedonic (vs. utilitarian) products, and new (vs. mature) products. In particular, the performance quality of services (e.g., hotel stays, restaurant dinners) is usually more difficult to assess before purchase than that of goods (Murray and Schlacter 1990; Zeithaml 1981). Because eWOM may replace information obtained through sampling or purchase, consumers may rely more on eWOM for services than for goods to reduce perceived functional risk (Murray 1991). Similarly, functional risk is higher for hedonic products, which are pleasant and enjoyable and appeal to the senses (e.g., perfume) (Dhar and Wertenbroch 2000), and consumers experience and assess them more subjectively than utilitarian products (which are useful and practical, e.g., vacuum cleaners). Electronic word of mouth can reduce this risk by helping "consumers identify the products that best match their idiosyncratic preferences" (Moe and Trusov 2011, p. 444). Functional risk is also higher for newly introduced products because it is difficult to anticipate their performance. For these products, WOM plays a particularly important role in building product awareness and providing information to consumers (Mahajan, Muller, and Kerin 1984).

Financial risk reflects the money it takes for consumers to make the product work properly or to replace it if it fails or does not meet expectations (Roselius 1971). In the case of high financial risk, consumers rely more heavily on eWOM (Lin and Fang 2006).

Which eWOM Metric Is More Effective?

Electronic word of mouth has been measured in practice and operationalized in extant academic literature in multiple ways to capture different aspects. We distinguish among the following eWOM metrics: volume, valence, composite valence–volume, variance, and other. Electronic word of mouth volume measures "the total amount of eWOM interaction" (Liu 2006, p. 75)—that is, the total number of eWOM units sent about a particular object. Because eWOM volume inherently delivers information about how many other people have experienced or used the product and how popular the product is in the market, it can increase consumers' awareness of and reduce their uncertainty about the product, ultimately leading to an increase in sales (Chen, Wang, and Xie 2011; Chintagunta, Gopinath, and Venkataraman 2010; Park, Gu, and Lee 2012). The underlying dynamic is the bandwagon effect (e.g., Van den Bulte and Lilien 2001), in which the mere availability of other consumers' opinions has an influence on other consumers, regardless of whether these opinions are positive or negative (Godes and Mayzlin 2009; Xiong and Bharadwaj 2014). The main idea behind the reliance on the amount of peer-generated information in consumers' decision-making process is rooted in herding behavior and social impact theory, according to which people tend to follow the previous behavior of others to reduce risk in the environment (Banerjee 1992; Latané 1981). In addition, the more consumers discuss a product, the greater the chance that other consumers will become aware of it, because message repetition attracts people's attention to the topic of the message (Cacioppo and Petty 1989; Tellis 1988).

Valence is "the idea that eWOM can be either positive, negative, or neutral" (Liu 2006, p. 75). It is also called the "favorability," "sentiment," or "polarity" of eWOM and refers to both objective information found in the eWOM message (e.g., "The hotel room was infested with cockroaches") and the affect expressed therein (e.g., "I hated that movie!"). In this case, consumers' preferences for the product are formed, reinforced, or altered from the exposure to (un)favorable eWOM, which is indicative of a product's reputation and expected product quality (Kim and Gupta 2012; Liu 2006). Research refers to this as the persuasion effect or informational influence of eWOM (Godes and Mayzlin 2009; Rui, Liu, and Whinston 2013). Valence has been captured in various ways, some of which may be theoretically contaminated with measures of eWOM volume. Whereas operationalizations using relative terms, such as the ratio of positive tweets (e.g., Hennig-Thurau, Wiertz, and Feldhaus 2014) or the percentage of one-star ratings (e.g., Chen, Wang, and Xie 2011), are a nonconfounded representation of sentiment (positive or negative valence), operationalizations using absolute terms, such as the number of positive tweets (e.g., Hennig-Thurau, Wiertz, and Feldhaus 2014) or the number of one-star ratings (e.g., Chevalier and Mayzlin 2006), indicate both volume and valence.

Thus, we introduce a new metric labeled "composite valence–volume" (with two submetrics: positive volume and negative volume). This composite measure represents the combined influence of persuasion and bandwagon effects. For example, seeing that a product received 500 Facebook "likes" informs a consumer about the sentiment toward the product while also providing an indication about the actual number of people who formed an opinion about it. This represents both valence and volume. In contrast, the metric percentage of one-star ratings indicates that some consumers share negative sentiment, but it does not communicate how many consumers share an opinion. This is a measure of valence.

A less commonly investigated eWOM metric is variance, which represents "a natural measure to capture the heterogeneity in consumer opinions [such that] upon seeing a high variance, consumers infer that the product is a niche one that some people love *and* others hate" (Sun 2012, p. 697; emphasis added). Low variance of eWOM means that consumers agree that the product is either good *or* bad, which explains why the effect of eWOM on sales can be either positive or negative.

Finally, a range of other metrics exists, including the mere presence of consumer-generated information on a particular platform (eWOM existence) and specific words and phrases, such as the word "award" in movie-related eWOM (eWOM content). In summary, we expect that platform characteristics, product characteristics, and metrics, as well as their interplay, moderate the impact of eWOM on sales.

METHODOLOGY

Collection and Coding of Studies

To identify the empirical studies investigating the effects of eWOM on sales, we conducted a rigorous and thorough literature search. We checked several online scientific databases, including SSR, ABI Inform, and EconLit, and carried out an issue-by-issue search of the top journals in three streams of research: (1) marketing, (2) economics and management, and (3) information systems and computer science. We also searched for unpublished work, including dissertations and working papers in databases, such as the ProQuest Dissertation Express, MSI, SSRN, EconPapers, REPEC, and AISeL, as well as papers in the proceedings of the most prominent conferences in the specified research fields. Next, we scanned the Internet using Google Scholar. Because eWOM has a myriad of aliases, we used the following keywords in the search process: "buzz," "consumer-generated content," "electronic word of mouth," "eWOM," "online opinion," "online rating," "online recommendation," "online review," "online word of mouth," "online WOM," "peer recommendation," "user comments," "user-generated content," "user ratings," "user review," and "social earned media." We applied a snowballing procedure, in which we examined the references in the publications obtained to find additional studies. Moreover, we corresponded with the researchers represented in the original data set, requesting additional information and inviting related studies on the topic. Finally, we posted messages calling for additional studies on the electronic mailing list ELMAR.

After completing the search process on December 1, 2014, we excluded theoretical papers, qualitative investigations, and quantitative studies that did not report findings on the outcomes of eWOM but investigated only its antecedents. We further restricted the focus of our analysis to work examining the impact of eWOM on objective measures of performance, such as the number of product units sold and revenues from sales of firm-created products and services, while excluding those assessing consumer product evaluations, purchase intentions, television viewership, free online music sampling, sales distributions, growth rates, and forecasts. The final data set consists of 1,532 effect sizes, retrieved from 96 studies (see the Web Appendix).

The average number of effect sizes reported per study is 16, with a minimum of 1 and maximum of 260. The division of effect sizes over the three major research streams is as follows: information systems and computer science (52%), marketing (36%), and economics and management (12%). Our sample includes 55 articles (57%) published in 25 journals, as well as 20 conference proceedings papers (21%), 16 working papers (17%), and 5 doctoral dissertations (5%), all published between 2004 and 2014 (with data collected between 1999 and 2013).

We developed a transparent and replicable coding protocol containing a detailed coding manual with descriptions of each variable. A single coder was trained to code all the studies. To ensure the reliability of coding, another coder independently coded a subsample of 920 effect sizes and related variables. The Cohen's kappa coefficient of interrater reliability is .97, which is satisfactory (Landis and Koch 1977), and disagreements were solved through discussion.

Operationalization of sales. The sales variable was operationalized in six ways in the primary studies: sales rank (60.5%), number of customers or product units sold (11%), total sales (12.5%; i.e., sum of online and offline sales), offline sales (7.5%), online sales (5.5%), and percentage of opening-weekend revenues of total revenues (3%). When sales rank was used as the dependent variable, we changed the sign of the effect size to account for the inverse relationship of this measure to actual sales (Brynjolfsson, Hu, and Smith 2003) unless corrections were already undertaken in the primary studies.[2]

Platforms. In the primary studies, eWOM was collected on more than 40 different online platforms: Allocine.fr, Amazon (U.S., U.K., and German versions), Apple and Google app stores, Autobytel, Barnes & Noble, Car and Driver, CNET, ConsumerReports.org, Ctrip, Dangdang, Delicious, Digg, DpReview, eBay, Edmunds.com, Epinions, Facebook, GameSpot (i.e., VideoGames.com), Gforums, HowardForums.com, Internet Movie Database, Kiva friends, MSN, MySpace, Naver, Netflix, Plurk, Rotten Tomatoes, Taobao, Tongcheng (17u), TStore, Twitter, Yahoo!Movies, Yelp, YouTube, several unnamed e-commerce platforms (in Asia, Europe, and North America), various blogs, and the Internet in general. The most frequently investigated platforms are Amazon (44%), Barnes & Noble (12%), and Yahoo!Movies (10%). We capture variation across all the platforms further using a set of platform characteristics discussed subsequently.

[2]Because Amazon sales rank rates the best-selling products with a lower number, this measure represents an inverse of actual sales. When Amazon sales rank was used as the dependent variable, we searched for information about potential corrections; if we were unable to find any, we changed the sign of the effect size to account for the inverse relationship of this measure to actual sales. Some authors already use available approximations of (online) sales based on Amazon sales rank ($\log[\text{sales}] = \beta_1 + \beta_2 \times \log[\text{sales rank}] + \varepsilon$) (Brynjolfsson, Hu, and Smith 2003; Chevalier and Goolsbee 2003; Ghose, Smith, and Telang 2006), in which cases we treat these as online sales and do not correct the effect sizes in the aforementioned way. We provide several examples of effect size computations in the Web Appendix.

Products. Electronic word of mouth collected in the primary studies is related to 26 product categories: audio players, apparel, books, cars, cellular phone devices, cellular phone services (e.g., prepaid cards), computer memory, digital cameras, electronics, financial services (microloans), furniture, garden products, green tea, hotel stays, houseware, Internet services, mobile applications, movies, music albums, perfume, restaurant services, software, video cassettes and DVDs (rental and purchase), video games, and video players. The majority of the effects are related to outcomes in three main product categories: books (39%), movies (20%), and digital cameras (8%). Services represent 24% of the products in our data set. Hedonic products make up 39% of the sample. While products were analyzed at different stages of their life cycle, as many as 37% of the effects are for newly introduced goods and services; 21% are products that carried high financial risk at the time of the primary data collection.

Metrics. Most researchers captured eWOM mainly by eWOM volume (used in 88% of the studies) and valence (used in 81% of the studies) while paying limited attention to variance (used in 18% of the studies) and other eWOM metrics (i.e., mere existence of eWOM or specific words contained in a textual post were used in 16% of the studies). In addition, we find that eWOM was operationalized as a composite variable containing elements of both valence and volume—namely, as the number of positive/negative posts containing eWOM (used in 14% of the studies). So far, the primary studies labeled such a variable as either valence or volume, even though it represents a combination of these two measures and is coded as a composite variable in this article. Furthermore, 12% of the studies investigated eWOM by focusing on one metric only, while the vast majority of the studies used multiple metrics for eWOM. We find great variation in the way extant literature operationalized each of these variables, and we classify (1) each volume measure as an average, an incremental, or a cumulative measure; (2) each valence and composite valence–volume measure as positive or negative; and (3) each variance measure as agreement and precision, variability, or incremental.[3]

Control variables. Multiple methodological and study characteristics could also moderate the effects of eWOM on sales, including the type of endogeneity controls, operationalization of the dependent variable, and other study characteristics. Furthermore, omitting from the estimation models other variables that are known to affect sales, such as marketing-mix controls, may lead to erroneous results (for a review of relevant confounding variables, see Van den Bulte and Lilien 2001). Therefore, we include these as control variables in our study.

Primary Data Collection

To investigate the moderation effects of platform characteristics, we collected primary data by visiting the platforms at the time of the original data collection using the Wayback Machine. We trained three coders to collect information on all online platforms from our sample and to evaluate the platform characteristics in terms of sender details, message details, platform maturity, and eWOM posting costs. For sender details, we created vectors for homophily and trustworthiness (Metzger, Flanagin, and Medders 2010). Electronic word of mouth sender homophily captures the presence of cues that can help receivers assess their similarity to eWOM senders according to their username, avatar, profile page, and geographic location. Sender trustworthiness is based on real names, duration of platform membership, and contact information. For message details, we created a vector that consists of two variables: the proportion of eWOM with a time stamp and the proportion of eWOM with a helpfulness rating. In addition, we coded eWOM visibility (the number of scrolls needed to access eWOM), structured display of eWOM (e.g., having summary sections), the year of platform introduction, and eWOM posting costs (when purchase or registration is required before a consumer can provide eWOM) (for details, see the Web Appendix).[4]

In addition to these platform characteristics, we code information related to products' perceived risk. Three marketing experts classified each product category in our sample as hedonic or utilitarian. Furthermore, they assessed the product categories' financial risk at the time of the original data collection. As a result, these product-related variables are also time varying (e.g., digital cameras were coded differently for the year of their market introduction than for more recent years because the financial risk related to their purchase had decreased). Table 3 provides the operationalization of all variables, and the Web Appendix reports the correlation matrix and the descriptive statistics.

Meta-Analytic Calculations

Computation of effect sizes. To measure the effect size of eWOM on sales, we use (bivariate and partial) correlations, which is a common approach for meta-analytic reviews in marketing and management (e.g., Carney et al. 2011; De Matos and Rossi 2008; Heugens and Lander 2009). In contrast, Floyd et al. (2014) and You, Vadakkepatt, and Joshi (2015) use elasticities. Conducting a meta-analysis using correlations instead of elasticities offers two advantages. First, the interpretation of correlations is independent of the measurement scale (Eisend 2006; Lipsey and Wilson 2001). This is important when examining the effects of various eWOM metrics on sales because both the dependent measures (e.g., Amazon sales rank vs. box-office revenues) and the eWOM metrics used in primary studies are diverse in both nature and scale. In particular, eWOM volume metrics are usually measured in absolute terms, whereas eWOM valence metrics are usually measured on a five-point rating scale. As Van Heerde, Gupta, and Wittink (2003) and Van Heerde (2005) show, elasticity may not be comparable across variables (e.g., X_1 and X_2), because a

[3]To provide a complete overview of the relative importance of the different metrics used in the literature, in the HOMA we also include two other eWOM submetrics (i.e., existence and content).

[4]When eWOM was collected from multiple platforms, unspecified platforms (e.g., blogs), or the Internet overall, we proceed in the following way: For multiple platforms (e.g., Ctrip and Tongcheng), we code the platform characteristics for each individual platform separately at the moment of data collection in the primary study and for the specific product category. We then average their values. For unspecified platforms or the Internet in general, we use the mean of our sample as a missing value imputation. In addition, we rerun the HiLMA model, excluding these cases altogether (174 cases in total) and using an alternative missing value imputation (i.e., the median instead of the mean). All three approaches yield the same results.

Table 3
VARIABLES IN THE HiLMA

Variable	*Description and Operationalization*
Platforms	
Platform Type[a]	
e-Commerce sites	Dummy variable that assumes the value of 1 if the online platform from which eWOM was collected is a e-commerce site (e.g., Amazon, CNET, eBay), and 0 otherwise.
Review sites	Dummy variable that assumes the value of 1 if the online platform from which eWOM was collected is a noncommercial review site (e.g., Epinions, Gamespot, Yahoo!Movies), and 0 otherwise.
Other platforms	Dummy variable that assumes the value of 1 if the online platform from which eWOM was collected is not specified or Internet overall, and 0 otherwise.
Amazon	Dummy variable that assumes the value of 1 if the online platform from which eWOM was collected is Amazon (Amazon.com, Amazon.de, Amazon.uk), and 0 otherwise.
Details Related to...	
eWOM sender: homophily	Presence of cues pertaining to the eWOM sender's similarity to the eWOM receiver is operationalized as a vector (continuous variable, mean-centered) of four continuous variables capturing the relative number of instances (1) when eWOM senders' geographic location is displayed, (2) when eWOM senders have a profile page, (3) when eWOM senders' usernames are displayed, and (4) when eWOM senders have an avatar. These instances are relative to the number of eWOM messages available on the first page accessed through Wayback Machine for a given product category at the moment of the data collection in the primary study (e.g., Amazon.de books in March 2008, Amazon.uk music albums in December 2006, Amazon.com digital cameras in March 2007). If, in four out of six book reviews available on the landing product page on Amazon, the reviewer's geographic location is specified, variable 1 is coded as .67; values for variables 1–4 are summed to create the vector.
eWOM sender: trustworthiness	Presence of cues pertaining to the eWOM sender's trustworthiness is captured as the sum of three continuous variables indicating how often (1) eWOM senders' real names are displayed, (2) the duration of eWOM senders' memberships within the platform is displayed, and (3) it is possible to contact eWOM senders through e-mail or private message. The number of instances is relative to the number of eWOM messages available on the first page accessed through Wayback Machine for a given product category at the moment of the data collection in the primary study.
eWOM message recency and helpfulness rating	Presence of additional information about the eWOM message. It is operationalized as a vector (continuous variable; mean-centered) of two variables indicating (1) whether a time stamp is displayed for eWOM on this platform, and (2) whether a helpfulness rating is displayed for eWOM on this platform (based on Wayback Machine).
eWOM visibility	Number of scrolls needed with a computer mouse to visualize eWOM information (continuous variable, mean-centered) (based on Wayback Machine).
eWOM structured display	Dummy variable indicating whether on a particular platform eWOM is organized into categories, provided with titles or summary sections (based on Wayback Machine).
Other Characteristics	
Platform maturity	Number of years since the online platform's introduction at the time of the data collection. It is calculated by subtracting the year of data collection from the year of the online platform introduction (continuous variable; mean-centered).
eWOM posting costs	Dummy variable indicating whether eWOM senders incur posting costs on a particular online platform (based on Wayback Machine).
Products	
Product Type[b]	
Service	Dummy variable indicating whether the product whose sales is examined is an intangible, perishable good that is inseparable from its provider.
Digital product	Dummy variable indicating whether the product whose sales is examined is an intangible good that exists in digital form.
Other Product Characteristics	
Financial risk	Variable on a 1–5 Likert scale that assumes the value of 1 if the product carries very low financial risk (e.g., mobile apps) and 5 if it carries very high financial risk (e.g., cars) (mean-centered). Products are classified on the basis of their historical price at the time of the primary data collection using one of the following sources: (1) average prices reported in primary studies; (2) representative prices through the Wayback Machine for the product, time, and geographic location of the data collection (e.g., Amazon.uk, Edmunds.com); and (3) other sources (e.g., Tomshardware.com). Then, three coders classified all products on a 1–5 Likert scale according to the relative prices in our sample—1 for lowest prices (e.g., mobile apps) and 5 for highest prices (e.g., cars). Agreement was reached through discussion.
Hedonic product	Dummy variable that assumes the value of 1 if the product is predominantly hedonic and 0 if it is predominantly utilitarian. Three coders classified all products, and agreement was reached through discussion.
Stage in the Product Life Cycle	
New product	Dummy variable that assumes the value of 1 if the product whose sales is examined is reported in the primary study as newly introduced at the time of the original data collection, and 0 otherwise.

Table 3
CONTINUED

Variable	*Description and Operationalization*
Metrics	
Volume	
Cumulative volume	Dummy variable indicating whether eWOM was operationalized as the total amount of eWOM available at a particular time, including past periods and, in some cases, the current period (reference in the model).
Incremental volume	Dummy variable indicating whether eWOM was operationalized as the difference in the total or average amount of eWOM between two periods.
Average volume	Dummy variable indicating whether eWOM was operationalized as average number of eWOM per product.
Valence	
Average valence	Dummy variable indicating whether eWOM was operationalized as an average aggregate measure.
Incremental valence	Dummy variable indicating whether eWOM was operationalized as the difference in the average ratings between two periods or between two online platforms.
Positive valence	Dummy variable indicating whether eWOM was operationalized as the (1) polarity (i.e., the ratio of positive to negative eWOM), (2) subjectivity (i.e., the ratio of positive to neutral eWOM), or (3) the ratio of positive eWOM to total eWOM.
Negative valence	Dummy variable indicating whether eWOM was operationalized as the (1) polarity (i.e., the ratio of negative to positive eWOM), (2) subjectivity (i.e., the ratio of negative to neutral eWOM), or (3) the ratio of negative eWOM to total eWOM.
Composite Valence–Volume	
Positive volume	Dummy variable indicating whether eWOM was operationalized as amount of positive eWOM.
Negative volume	Dummy variable indicating whether eWOM was operationalized as amount of negative eWOM.
Variance	
Agreement and precision	Dummy variable indicating whether eWOM was operationalized as the inverse of the variance in numerical ratings (i.e., precision of the ratings).
Variability	Dummy variable indicating whether eWOM was operationalized as average variance, or standard deviation in numerical ratings.
Incremental variance	Dummy variable indicating whether eWOM was operationalized as a difference in standard deviation of or average variance of numerical ratings.
Study Characteristics	
Endogeneity Controls[c]	
Simultaneous equations	Dummy variable that indicates with 1 if endogeneity was accounted for by using a Granger causality test or simultaneous equations model, and 0 otherwise.
First-difference model	Dummy variable that indicates with 1 if endogeneity was accounted for by using a first-difference model, and 0 otherwise.
Instrumental variables	Dummy variable that indicates with 1 if endogeneity was accounted for by using instrumental variables or a generalized-method-of-moments approach, and 0 otherwise.
Marketing Controls	
Price control	Dummy variable that assumes the value of 1 if product price was controlled for, and 0 otherwise.
Price promotion control	Dummy variable that assumes the value of 1 if price promotion was controlled for, and 0 otherwise.
Other Methodological Controls	
Year of data collection	Year of the data collection. If the data collection spans over the course of several years, we consider the mean year (continuous variable; mean-centered).
Number of parameters	Number of variables in the response model (continuous variable; mean-centered).
Lagged DV	Dummy variable indicating whether a lagged term of sales was included in the response model.
Sales rank	Dummy variable that assumes the value of 1 if sales was operationalized as sales rank, and 0 otherwise. Effect sizes signs were inverted when needed. Effect sizes from studies that converted sales rank into sales using the formula by Brynjolfsson, Hu, and Smith (2003) are coded as 0.
Top-tier publication	Dummy variable indicating whether the primary study has been published in a top-tier academic journal (*Journal of Marketing*, *Journal of Marketing Research*, *Marketing Science*, *International Journal of Research in Marketing*, *Management Science*, or *Information Systems Research*).
Standard error	Standard errors of the Fisher-transformed effect sizes (continuous variable; mean-centered).

[a]Ref = social media sites.
[b]Ref = tangible good.
[c]Ref = no endogeneity correction.
Notes: DV = dependent variable.

percentage change in X_1 is often not comparable to a percentage change in X_2, which is an important limitation of using elasticities in a broad meta-analysis. We argue that when comparing metrics on the basis of very different measurement scales, correlations enable a more informative and objective comparison.

The second advantage stems from the observation that elasticity cannot be computed for a large number of studies in our sample, because necessary effect size statistics (typically, the averages of the dependent and explanatory variables) were not reported in the primary study and could not be obtained from the authors. As Peterson and Brown (2005) note, the inclusion of effect sizes based on partial correlations reduces both sampling errors because of the increased number of effect sizes and nonsampling errors because of the inclusion of a broader array of research designs. Thus, by using correlations (i.e., a scale-free measure that can be computed on the basis of a wide range of statistics), we broaden the scope of the meta-analysis to 1,532 effect sizes obtained from 96 studies covering 40 platforms and 26 product categories.

The impact of eWOM on sales is captured by bivariate Pearson product-moment correlations (r) and partial correlation coefficient effect sizes ($r_{xy,z}$; Lipsey and Wilson 2001; Rosenthal 1988),[5] where 89% of the effects were based on partial correlations. The partial correlations are based primarily on regression-type models that assess sales as the dependent variable, using a variety of explanatory variables, including eWOM metrics.[6]

We transform all correlation coefficients into Fisher's Z effect sizes (z_r) because they are easy-to-interpret scale-free measures that have the desirable statistical properties of being approximately normally distributed with a sample variance that depends only on sample size and not on the population correlation itself.[7] Furthermore, because the studies in our sample vary in the number of observations, we weight each effect size by its inverse variance to give more weight to more accurate measures (Lipsey and Wilson 2001; Shadish and Haddock 2009).[8]

HOMA. In line with meta-analytic standards, we first summarize the overall effects of eWOM using a random-effects HOMA for combining study estimates (Carney et al. 2011; Geyskens et al. 2009). To estimate mean effects, we account for differences in the precision of the retrieved effect sizes by using weights (w; Hedges and Olkin 1985). We also use these weights to calculate the standard error and confidence interval of the mean effect.

HiLMA. Systematic attenuating statistical artifacts other than sample size are corrected for during HiLMA procedures (Lipsey and Wilson 2001). The HiLMA is preferable to more conventional subgroup moderator analyses for its use of a multivariate, regression-based format (Carney et al. 2011; Geyskens et al. 2009; Tellis 1988). This procedure enables us to filter out the effects of important moderators that were or were not part of the primary studies. In our case, we collected platform and product data from additional sources to explain heterogeneity across effect sizes. In the HiLMA, we consider four comprehensive sets of moderating variables to explain the variation in the correlation between eWOM and sales: (1) platform-related factors, (2) product-related factors, (3) eWOM metrics, and (4) characteristics of the studies in our sample. As a rule, we include in our analysis only variables that are employed in at least seven regression models.

The model contains ten variables representing platform characteristics. These include three dummies for platform type (for review platforms, e-commerce platforms, and other, with social media platforms used as reference), eWOM sender details (homophily and trustworthiness vectors), eWOM message details (vector for time stamp and helpfulness rating), eWOM message visibility, structured display of eWOM, platform maturity, and the imposition of eWOM posting costs.[9] Five variables are related to product characteristics (two dummies for services and digital products, with tangible goods as the reference; a dummy for hedonic products; a five-item Likert scale indicating the level of financial risk; and a dummy for newly introduced products). We use 11 dummies to capture eWOM submetrics (average volume, incremental volume, average valence, incremental valence, positive valence, negative valence, positive volume, negative volume, agreement and precision, variability, and incremental variance, with cumulative volume as the reference). The model also includes 12 variables that account for the differences in methodological choices made in the primary studies. Table 3 describes the operationalization of all variables. To account for the statistical dependencies among effect sizes based on the same subject samples, we follow Bijmolt and Pieters (2001) and estimate a hierarchical random-effects meta-analytic model to control for within-study correlation.

RESULTS

HOMA Results

The 1,532 back-transformed Z effect sizes span across a large range, from highly negative (–.69) to highly positive (.98; M = .08, SD = .18). We observe 52.5% significant and positive effects (807 effects), 11% significant and negative effects (165 effects), and 36.5% nonsignificant effects (560 effects). These mixed results highlight the great variation in the effects of eWOM on sales and call for a formal analysis to assess the *overall* impact of eWOM (HOMA) (see the Web Appendix and Table 4). From the random-effects HOMA, we conclude that there is an overall significant and positive relationship between eWOM and

[5]We use the following formula to compute the partial correlation coefficient effect size (Rosenthal 1988, p. 25): $r_{xy,z} = t/\sqrt{(t^2 + d.f.)}$, where t is the t-value associated with the regression parameter that captures the effect of eWOM on sales and d.f. are the degrees of freedom of the reported regression model.

[6]Bivariate correlations and partial correlations are potentially different because the latter are computed while controlling for other explanatory variables. Therefore, as a robustness check, we include a dummy variable to capture the mean difference between both types of correlations and include several moderators indicating whether specific other explanatory variables were controlled for when computing the partial correlation. These variables were not significant, so we removed them from the model. The full set of results is available on request.

[7]We transform average effect sizes (HOMA) and regression estimates (HiLMA) back into a standard correlational form (r) for ease of interpretation as well as to avoid overestimation of the population value of z (Silver and Dunlap 1987). We use the following formulae for Fisher's Z: (1) transformation: $z_r = 1/2 \log([1 + r]/[1 - r])$ (Rosenthal 1988, p. 27) and (2) back-transformation to correlation units: $r = (e^{2z} - 1)/(e^{2z} + 1)$ (Lipsey and Wilson 2001, p. 64).

[8]We calculate the weight, w, as follows: $w_i = 1/(se_{z_r}^2 + \hat{v}_\theta)$, where se is the standard error of the effect size, which we calculate as $se_{z_r} = -1/\sqrt{(n - 3)}$, and $\hat{v}_\theta$ is the random-effects variance component. We calculate the meta-analytic mean effect size as follows: $\overline{z_r} = \Sigma\,(w \times z_r)/\Sigma w$, where its standard error is $se_{\overline{z_r}} = \sqrt{(1/\Sigma w)}$ and its 95% confidence interval is computed as: lower CI = $\overline{z_r} - 1.96\,(se_{\overline{z_r}})$ and upper CI = $\overline{z_r} + 1.96\,(se_{\overline{z_r}})$.

[9]In addition, because more than 40% of observations in our sample are from Amazon, we filter out potential platform-specific effects by including an Amazon dummy variable in the moderator analysis (HiLMA).

Table 4
HOMA RESULTS

Variable	*k*	*Number of Studies*	*N*	*+ and Significant*	*– and Significant*	*Weighted Average Random-Effect r (SE)*	*Q*	*I^2*
Overall	1,532	96	2,391,602	807	165	.091 (.006)***	666,138***	.998
Platforms								
Social media platforms	275	24	151,385	172	22	.132 (.009)***	16,351***	.983
Review platforms	237	29	175,852	132	31	.121 (.013)***	29,235***	.992
E-commerce platforms	1,001	55	2,176,362	493	110	.071 (.008)***	618,496***	.998
Products								
Tangible good	1,027	53	2,023,557	517	112	.070 (.008)***	608,260***	.998
Service	368	33	271,479	195	47	.146 (.011)***	49,488***	.993
Digital product	109	14	59,040	73	2	.108 (.012)***	3,440***	.969
Utilitarian product	939	52	1,918,803	453	105	.064 (.008)***	589,672***	.998
Hedonic product	593	52	483,964	354	60	.136 (.008)***	76,162***	.992
High financial risk	320	36	633,557	226	28	.149 (.022)***	427,431***	.999
Low financial risk	1,212	71	1,760,050	581	137	.074 (.004)***	185,834***	.993
Mature product	966	57	1,541,559	509	95	.071 (.005)***	180,193***	.995
New product	566	41	850,043	298	70	.127 (.015)***	453,680***	.999
Metrics								
eWOM Volume	589	84	2,277,093	399	52	.141 (.014)***	527,364***	.999
Average	7	3	117,734	6	0	.360 (.074)***	5,536***	.999
Incremental	144	14	106,831	48	16	.059 (.016)***	8,764***	.984
Cumulative	438	70	2,053,045	345	36	.161 (.017)***	509,939***	.999
eWOM Valence	596	78	2,264,176	248	63	.049 (.003)***	30,702***	.981
Average rating	312	62	1,583,339	189	30	.075 (.005)***	23,997***	.987
Incremental rating	139	7	539,918	22	5	.021 (.006)***	461***	.700
Positive valence	91	23	698,721	30	4	.036 (.006)***	1,823***	.951
Negative valence	54	16	662,214	7	24	–.013 (.005)*	780***	.932
eWOM Composite Valence–Volume	108	13	56,620	41	19	.061 (.020)**	4,612***	.977
Positive volume	66	13	56,620	37	2	.140 (.026)***	3,999***	.984
Negative volume	42	9	10,865	4	17	–.064 (.019)***	227***	.819
eWOM Variance	137	17	944,404	59	19	.061 (.009)***	11,068***	.988
Agreement and precision	13	2	5,908	1	8	–.023 (.073)	741***	.984
Variability	42	13	937,484	30	5	.117 (.016)***	9,935***	.996
Incremental	82	2	1,012	28	6	.041 (.010)***	251***	.677
Other eWOM Measures	102	15	150,000	60	12	.102 (.014)***	6,753***	.985
Existence	27	8	76,078	18	5	.105 (.025)***	1,807***	.986
Content	75	8	87,684	42	7	.101 (.017)***	4,737***	.984

*$p < .05$.
**$p < .01$.
***$p < .001$.
Notes: The table reports back-transformed Fisher's Z correlations; positive and negative valence measures can be both average (e.g., five-star or one-star rating) and incremental (e.g., the change of the percentage of positive messages). k = number of effect sizes; N = total sample size; +/– and significant = number of positive/negative and significant effect sizes; Q = Cochran's homogeneity test statistic; I^2 = scale-free index of heterogeneity. The significance level of effect sizes is based on t-values (for partial correlations) and p-values (for bivariate correlations).

sales ($\bar{r}^o = .091$, $p < .001$), which is nonnegligible (Aloe and Thompson 2013). This result is consistently positive across the different platforms and products.

Overall, we find more positive and statistically significant effect sizes for volume than for valence (26% vs. 16%), as well as higher weighted average random-effects correlations (for the overall measures: $\bar{r}^o = .141$ vs. .049; for the different submetrics [e.g., average volume vs. average rating]: $\bar{r}^o = .360$ vs. .075). Although a formal model is required to filter out potential confounding effects and assess whether the effects across different metrics are significantly different, the HOMA results provide first evidence that the volume of consumer-generated content ($\bar{r}^o = .141$, $p < .001$) is more strongly related to sales than all other eWOM operationalizations: valence ($\bar{r}^o = .049$, $p < .001$), composite valence–volume ($\bar{r}^o = .061$, $p < .01$), variance ($\bar{r}^o = .061$, $p < .001$), and other eWOM measures ($\bar{r}^o = .102$, $p < .001$). In addition, the HOMA results provide evidence that negative eWOM is not critical, given the low correlations with sales for negative valence ($\bar{r}^o = -.013$, $p < .05$). For negative volume ($\bar{r}^o = -.064$, $p < .001$), however, the negative effects are more pronounced, underscoring the importance of differentiating between relative and absolute measures of eWOM.

Furthermore, the significant Cochran's Q-test of homogeneity and the high scale-free index of homogeneity I^2 confirm a substantial amount of heterogeneity, implying that the variability of the effect sizes is larger than would be expected from subject-level sampling error alone. Overall, the results of the HOMA show that eWOM significantly affects sales, but the direction, size, and statistical significance of the average effects differ between and within the main eWOM metrics, calling for a moderator analysis.

HiLMA Results

In this section, we show how the link between eWOM and sales differs across platforms, products, eWOM metrics, and other study characteristics. Because we find significant differences *across* platform and product characteristics in the overall-sample analysis, we conduct additional moderator analyses *by* platform and product characteristics (moderated-moderation or three-way interaction) to further investigate possible interaction effects. Because adding interaction terms to the model leads to high levels of multicollinearity, we conduct a series of split-sample analyses by running the model separately for (1) social media platforms, (2) review platforms, (3) e-commerce platforms, (4) tangible goods, (5) services, (6) hedonic products, (7) utilitarian products, (8) new products, (9) mature products, and, finally, products with (10) high and (11) low financial risk. We report the results in Table 5 and summarize the key insights in Table 6.

We fill the gaps in the literature and address inconsistencies by conducting a moderator analysis on 1,430 effects across the different platforms, products, and the four key eWOM metrics (93% of our total sample).[10] The model fit is satisfactory (pseudo-R^2 = .26) and in line with prior meta-analyses (e.g., Bijmolt, Van Heerde, and Pieters 2005). Overall, multicollinearity does not severely affect the model. The highest reported variance inflation factor (VIF) is 8.37 for the year of data collection (average VIF = 3.07, median VIF = 2.37), and the results remain unaltered when removing this control variable. Moreover, the analysis of the correlation matrix (see the Web Appendix) indicates that the highest correlation is –.73 between e-commerce platforms and services. We detail our robustness checks, as well as our approaches to dealing with publication bias, in the Web Appendix. These checks confirm the stability of our results. Table 5 shows the back-transformed estimates (β) of the HiLMA, as well as the resulting back-transformed predicted correlations ($\bar{r}$) computed by setting all other variables at their sample means and, in the case of continuous variables, their upper and lower quartiles. In the next section, we discuss the key findings from Table 5 row by row.

Platform characteristics amplifying the impact of eWOM on sales: e-commerce platforms. Overall, Table 5 shows that the impact of eWOM on sales is stronger for e-commerce platforms (β^o = .100; $p < .05$; $\bar{r}^o$ = .052) than social media platforms, while eWOM effectiveness on review platforms does not significantly differ from that on social media or e-commerce platforms.[11] We argue that this result can be explained by the nature of these different platforms and how they are commonly used by consumers. E-commerce and review platforms are primarily designed to support consumers' decision journeys, whereas social media sites help maximize social exchanges (Schweidel and Moe 2014). Moreover, for new products (β^n = .263; $p < .0001$; $\bar{r}^n$ = .253) and, marginally, for utilitarian products (β^u = .105; $p < .10$; $\bar{r}^u$ = .081) eWOM displayed on e-commerce platforms is more effective than on social media platforms.

Platforms with more details that enable consumers to better assess their similarity to the eWOM sender exhibit a higher link to sales (β^o = .048; $p < .05$; $\bar{r}^o_{low}$ = .002; $\bar{r}^o_{high}$ = .050), especially when eWOM appears on social media platforms (β^{sm} = .061; $p < .0001$; $\bar{r}^{sm}_{low}$ = .138; $\bar{r}^{sm}_{high}$ = .166). In addition, eWOM displayed on platforms that offer more homophily details is particularly impactful on the sales of hedonic products (β^h = .050; $p < .10$; $\bar{r}^h_{low}$ = .082; $\bar{r}^h_{high}$ = .132), new products (β^n = .124; $p < .01$; $\bar{r}^n_{low}$ = .027; $\bar{r}^n_{high}$ = .171), and both high and low financial risk products (β^{hf} = .120; $p < .10$; $\bar{r}^{hf}_{low}$ = .106; $\bar{r}^{hf}_{high}$ = .168; β^{lf} = .033; $p < .05$; $\bar{r}^{lf}_{low}$ = .066; $\bar{r}^{lf}_{high}$ = .099). Thus, for hedonic products and newly introduced products, homophily information reduces uncertainty about functional product performance. These results also suggest that homophily details will amplify the effect of eWOM at any price level. eWOM sender trustworthiness details amplify eWOM effectiveness only for review platforms (β^r = .193; $p < .10$; $\bar{r}^r_{low}$ = .027; $\bar{r}^r_{high}$ = .219). Overall, these findings reveal a stronger weight of homophily details than that of trustworthiness details influencing the effectiveness of eWOM.

Across the board, eWOM message details (time stamp and helpfulness rating) do not significantly moderate the link between eWOM and sales. Instead, eWOM visibility is of general importance for the entire sample (β^o = –.056; $p < .01$; $\bar{r}^o_{low}$ = .062; $\bar{r}^o_{high}$ = .005) and, in particular, for e-commerce platforms (β^e = –.054; $p < .05$; $\bar{r}^e_{low}$ = .104; $\bar{r}^e_{high}$ = –.004), utilitarian products (β^u = –.081; $p < .01$; $\bar{r}^u_{low}$ = .120; $\bar{r}^u_{high}$ = –.042), mature products (β^m = –.045; $p < .05$; $\bar{r}^m_{low}$ = .102; $\bar{r}^m_{high}$ = .013), and high-financial-risk products (β^{hf} = –.256; $p < .0001$; $\bar{r}^{hf}_{low}$ = .276; $\bar{r}^{hf}_{high}$ = .108).

Overall, the structured display of eWOM information is linked to lower sales (β^o = –.077; $p < .01$; $\bar{r}^o$ = –.044). This finding also emerges in the split-sample analyses for e-commerce platforms (β^e = –.093; $p < .01$; $\bar{r}^e$ = –.016), tangible products (β^t = –.090; $p < .01$; $\bar{r}^t$ = –.079), utilitarian products (β^u = –.099; $p < .01$; $\bar{r}^u$ = –.024), and new products (β^n = –.085; $p < .05$; $\bar{r}^n$ = .055). In general (across all of Table 5), platform maturity and eWOM posting costs are not significant, though eWOM posting costs moderate the impact of eWOM on sales for products with higher financial risk (β^{hf} = .216; $p < .05$; $\bar{r}^{hf}$ = .166).

Product characteristics amplifying the impact of eWOM on sales. Overall, we find no significant differences in the effectiveness of eWOM across tangible goods, services, and digital products, or between hedonic and utilitarian products. This is a notable finding that underscores the importance of measuring and managing eWOM for a broad range of products. The only exception is for services: eWOM in social media is particularly impactful on the sales of services (β^{sm} = .255; $p < .01$; $\bar{r}^{sm}$ = .287).

[10] We exclude effect sizes of eWOM content and existence on sales from the HiLMA model because there are not enough observations for these submetrics and because the results are too specific (e.g., the frequency of the word "advertising" in Japanese blogs) for generalization.

[11] This result is not driven by the platform-specific sales measures. Among effect sizes collected on e-commerce platforms, 13% are based on gross wholesale sales, whereas 18% of the effect sizes collected on social media platforms are based on site-specific sales. Notably, there is no statistical difference between the effect of eWOM on site-specific sales and gross wholesale sales among the e-commerce platforms (t-value = .42, p = .68) or the social media platforms (t-value = .85, p = .40), suggesting that the dominance of eWOM on e-commerce platforms is not driven by the criterion variable used in primary studies.

Table 5
HiLMA RESULTS

	Overall and by Platforms and Products[a]											
	Overall		*Social Media Platforms*		*Review Platforms*		*e-Commerce Platforms*		*Tangible Goods*		*Services*	
	β^o	$\bar{r}^o$	β^{sm}	$\bar{r}^{sm}$	β^r	$\bar{r}^r$	β^e	$\bar{r}^e$	β^t	$\bar{r}^t$	β^s	$\bar{r}^s$
Intercept	.176**	.023	.118	.164	.225*	.146	.295***	.067	.185*	.068	.074	.164
Platforms												
Social media platforms (ref)		−.049								−.020		.156
Review platforms[c]	.043	−.006							.032	.012	.023	.179
E-commerce platforms[c]	.100*	.052							.103	.083	−.123	.034
Other platforms[c]	−.124	−.173							−.160	−.180		
eWOM sender homophily details[b]	.048*	.002 .050	.061***	.138 .166	−.076	.178 .128			.045	.070 .094	.002	.162 .164
eWOM sender trustworthiness details[b]	−.001	.023 .022			.193†	.027 .219	−.011	.068 .062	−.039	.073 .053	.113	.096 .165
eWOM message time stamp and helpfulness rating[b]	−.018	.024 .016			.061	.106 .167	.038	.070 .080	−.006	.068 .066	−.020	.177 .158
eWOM visibility (scrolls)[b]	−.056**	.062 .005			−.050	.180 .147	−.054*	.104 −.004	−.045	.071 .036	−.076	.215 .166
eWOM unstructured display (ref)		.034				.174		.077		.099 .010		.175
eWOM structured display[d]	−.077**	−.044			−.087	.088	−.093**	−.016	−.090**	.079	−.053	.124
Platform maturity[b]	−.001	.024 .020							−.009	−.011		
No eWOM posting costs (ref)		.038						.084		.097		
eWOM posting costs[e]	−.026	.012					−.035	.049	−.064	.034		
Products												
Tangible good (ref)		.022		.035				.061				
Service[f]	−.012	.010	.255**	.287			−.030	.031				
Digital product[f]	.053	.075	.003	.038			.084	.144				
Utilitarian (ref)		.024						.065		.063		.064
Hedonic[g]	−.004	.020					.013	.077	.027	.090	.106	.169
Financial risk[b]	.054*	.012 .119	−.018	.167 .132	−.068	.159 .092	.058†	.055 .112	.047	.059 .151		
Mature product (ref)		−.003		.194				.049		.042		.135
New product[h]	.069*	.067	−.043	.152			.098*	.147	.136*	.177	.034	.169
eWOM Metrics												
Cumulative volume (reference)		.114		.214		.167		.173		.162		.219
Average volume[i]	−.031	.083										
Incremental volume[i]	−.036	.079	−.107**	.109	.161	.319	−.027	.147	−.019	.143	−.001	.218
Average valence[i]	−.220***	−.109	−.059**	.157	−.069*	.099	−.248***	−.077	−.242***	−.083	−.095***	.127
Incremental valence[i]	−.078**	.036					−.078**	.096	−.075**	.088		
Positive valence[i]	−.148***	−.034	−.070***	.145	−.034	.134	−.158***	.016	−.152***	.010	−.022	.198
Negative valence[i]	−.181***	−.069			−.076	.092	−.188***	−.015	−.185***	−.023	−.111*	.111
Positive volume[i]	−.007	.107	−.048	.167			−.119	.055	−.056	.108	−.138	.083
Negative volume[i]	−.153	−.040	−.297**	−.089			−.120	.055	−.128	.035	−.336†	−.126
Agreement[i]	−.192	−.080										
Variability[i]	−.271***	−.163					−.292***	−.125	−.289***	−.133		
Incremental variance[i]	−.008	.107					−.007	.166	.002	.164		
Study Characteristics												
Not Amazon (ref)		.015								.048		
Amazon[j]	.018	.032							.033	.081		
Year of data collection[b]	.001	.021 .025			.025	.050 .124						
No price control (ref)		.118				.122		.106		.113		.157
Price control[k]	−.162***	−.046			.257**	.367	−.049	.057	−.058†	.055	.180***	.328
No promotion control (ref)		.024						.076		.077		
Promotion control[l]	−.040†	−.016					−.209***	−.135	−.211***	−.136		
No lagged DV (ref)		.029						.076		.078		.151
Lagged DV[m]	−.067†	−.038					−.100*	−.025	−.101*	−.023	.225	.364
Sales DV (ref)		.049						.093		.097		
Sales rank[n]	−.044	.005					−.031	.062	−.036	.061		

Table 5
CONTINUED

Overall and by Platforms and Products[a]

	Overall		*Social Media Platforms*		*Review Platforms*		*e-Commerce Platforms*		*Tangible Goods*		*Services*	
	β^o	$\bar{r}^o$	β^{sm}	$\bar{r}^{sm}$	β^r	$\bar{r}^r$	β^e	$\bar{r}^e$	β^t	$\bar{r}^t$	β^s	$\bar{r}^s$
No endogeneity control (ref)		.052		.180		.177		.117		.109		.197
Simultaneous equation model[o]	−.003	.049	−.321***	−.150	−.007	.169	.029	.145	.025	.134	−.124†	.075
First-difference model[o]	−.118***	−.066					−.130***	−.014	−.118***	−.009		
IV or GMM[o]	.015	.067	−.002	.178	−.180*	−.003	.018	.135	.044	.153	−.199***	−.001
Number of parameters[b]	−.005**	.043 .008	−.012***	.212 .128	−.015***	.235 .132		.065 .068	1.4e-04	.069 .068	−.017***	.261 .116
Not a top-tier publication (ref)		.005		.148				.049		.051		.179
Top-tier publication[p]	.072†	.077	.085	.230			.076	.125	.066	.116	−.060	.120
Standard error[b]	.512	.007 .029	.861	.129 .232	.886	.115 .158	−.117	.070 .065	−.010	.069 .068	.398	.156 .187
k (N)	1,430 (96)		220 (24)		225 (26)		940 (55)		961 (53)		338 (32)	
−2 residual log-likelihood	2,244.5		−99.6		233.8		1,602.5		589.4		339.1	

By Products[a]

	Hedonic Products		*Utilitarian Products*		*New Products*		*Mature Products*		*High Financial Risk*		*Low Financial Risk*	
	β^h	$\bar{r}^h$	β^u	$\bar{r}^u$	β^n	$\bar{r}^n$	β^m	$\bar{r}^m$	β^{hf}	$\bar{r}^{hf}$	β^{lf}	$\bar{r}^{lf}$
Intercept	.078	.126	.250*	.064	−.063	.122	.129†	.071	.131	.101	.181***	.080
Platforms												
Social media platforms (ref)				−.025		−.011		.071				.070
Review platforms[c]			.020	−.005	.135*	.124	.030	.101			.030	.099
e-Commerce platforms[c]			.105†	.081	.263***	.253	.091	.161			.009	.078
Other platforms[c]			−.178	−.203			.020	.091				
eWOM sender homophily details[b]	.049†	.089 .137	.024	.065 .078	.124**	.027 .171	.036	.065 .091	.120†	.106 .168	.033*	.066 .099
eWOM sender trustworthiness details[b]	.023	.112 .131	.002	.064 .065	−.074	.167 .093	.071*	.063 .081	−.126†	.136 .094	.025	.073 .090
eWOM message time stamp and helpfulness rating[b]	−.055	.161 .107	.015	.064 .070	−.049	.153 .105	−.034	.071 .059			−.051†	.080 .062
eWOM visibility (scrolls)[b]	−.001	.126 .126	−.081**	.120 −.042	−.046	.153 .123	−.045*	.102 .013	−.256***	.276 .108	−.012	.089 .077
eWOM unstructured display (ref)		.119		.075		.139		.070				.079
eWOM structured display[d]	.036	.155	−.099**	−.024	−.085*	.055	.022	.092	−.091	.039	.012	.091
Platform maturity[b]	.001	.119 .127	.004	.063 .078	−.005	.147 .114					−2e-05	.080 .080
No eWOM posting costs (ref)				.084		−.036		.090		−.052		.096
eWOM posting costs[e]			−.046	.038	.205	.170	−.028	.062	.216*	.166	−.028	.068
Products												
Tangible good (ref)		.090		.055		.119		.073				.080
Service[f]	.047	.144	.129	.182								
Digital product[f]	−.024	.074	.073	.128	.046	.164	−.013	.059			.006	.085
Utilitarian (ref)						.019		.095				.082
Hedonic[g]					.148†	.167	−.034	.062			−.004	.078
Financial risk[b]	−.003	.127 .124	.070	.051 .188	.091†	.104 .280	−.010	.073 .054				
Mature product (ref)		.082								.073		
New product[h]	.067	.148							.098	.170		
eWOM Metrics												
Cumulative volume (reference)		.146		.169		.311		.088		.303		.125
Average volume[i]												
Incremental volume[i]	.114**	.256	−.077	.094	−.155	.164	.031	.119	.013	.315	.004	.129
Average valence[i]	−.098***	.049	−.248***	−.082	−.463***	−.177	−.051***	.038	−.447***	−.167	−.088***	.037
Incremental valence[i]			−.082**	.088			−.066***	.023			−.071***	.054
Positive valence[i]	−.010	.136	−.157	.013	−.107†	.212	−.139***	−.052	−.298*	.005	−.136***	−.012
Negative valence[i]	−.076*	.071	−.191***	−.022	−.203*	.116	−.168***	−.081	−.282*	.023	−.170***	−.046
Positive volume[i]	.144**	.284	−.133	.037	−.147	.173	.066	.153	−.086	.223	.026	.150

Table 5
CONTINUED

	By Products[a]											
	Hedonic Products		Utilitarian Products		New Products		Mature Products		High Financial Risk		Low Financial Risk	
	β^h	$\bar{r}^h$	β^u	$\bar{r}^u$	β^n	$\bar{r}^n$	β^m	$\bar{r}^m$	β^{hf}	$\bar{r}^{hf}$	β^{lf}	$\bar{r}^{lf}$
Negative volume[i]	−.057	.090	−.167	.002	−.240	.077	−.060	.028	−.147	.163	−.104	.021
Agreement[i]					−.415*	−.119					−.094	.031
Variability[i]	−.076**	.070	−.315***	−.154	−.564***	−.306	−.024	.064	−.533***	−.275	−.051**	.075
Incremental variance[i]			−.035	.135			.001	.089			−.003	.121
Study Characteristics												
Not Amazon (ref)								.071		.097		
Amazon[j]							−.007	.065	.011	.108		
Year of data collection[b]							.003	.066 .077				
No price control (ref)		.100		.107				.076				.096
Price control[k]	.149***	.246	−.052	.056			−.022	.054			−.028	.069
No promotion control (ref)		.126		.072		.139		.071		.115		.081
Promotion control[l]	.014	.139	−.214***	−.144	−.473***	−.358	−.013	.059	−.166	−.052	−.057*	.025
No lagged DV (ref)		.148		.070		.111		.096		.127		.082
Lagged DV[m]	−.174***	−.027	−.069	3.4E-04	.165	.272	−.134***	−.039	−.137	−.010	−.026	.056
Sales DV (ref)				.092								
Sales rank[n]			−.034	.058								
No endogeneity control (ref)		.144		.119		.146		.070		.152		.120
Simultaneous equation model[o]	−.094	.051	.021	.140	−.106	.041	−.032	.038			−.040	.081
First-difference model[o]	−.150	−.006	−.135***	−.015	−.276	−.135	−.139***	−.070	−.186	−.035	−.123***	−.003
IV or GMM[o]	−.059†	.086	−.017	.102	−.119	.028	.029	.099	−.085	.067	−.053†	.068
Number of parameters[b]	−.013***	.188 .090	.003	.055 .076	−.018***	.212 .105	−.002	.078 .062	.001	.096 .107	−.005***	.102 .064
Not a top-tier publication (ref)		.119		.059		.104		.066				.074
Top-tier publication[p]	.027	.145	.021	.080	.097	.199	.025	.091			.033	.107
Standard error[b]	.002	.126 .126	.206	.058 .066	−.376	.132 .100	.849	.036 .084	−.990	.184 .046	.513	.067 .086
k (N)	534 (52)		885 (52)		518 (41)		901 (57)		257 (36)		1,161 (71)	
−2 residual log-likelihood	399.0		1,493.8		1,077.0		593.2		1,654.1		339.4	

†$p < .10$.
*$p < .05$.
**$p < .01$.
***$p < .001$.
[a]Back-transformed unstandardized Fisher-Z transformed regression parameters are presented; interpret as correlations of eWOM with sales relative to the reference category. We removed from the analysis (1) variables with less than seven observations and (2) highly collinear variables. Results on all the variables (together with their VIF values) are available on request.
[b]All continuous variables are mean-centered.
[c]Ref = social media platforms.
[d]Ref = eWOM unstructured display.
[e]Ref = eWOM posting costs.
[f]Ref = tangible good.
[g]Ref = utilitarian good.
[h]Ref = mature product.
[i]Ref = cumulative volume.
[j]Ref = not Amazon.
[k]Ref = no price control.
[l]Ref = no promotion control.
[m]Ref = no lagged DV.
[n]Ref = sales DV.
[o]Ref = no endogeneity control.
[p]Ref = not a top-tier publication.
Notes: Two-sided tests of significance. k = number of effect sizes; N = number of studies; DV = dependent variable; IV = independent variable; GMM = generalized method of moments. The number of effect sizes and number of studies per variable are available in the Web Appendix.

In general, eWOM has a stronger link to the sales of new products than that of mature products ($\beta^o = .069$; $p < .05$; $\bar{r}^o = .067$), further demonstrating the importance of monitoring (and potentially stimulating) eWOM in the early stages of the product life cycle. The relevance of eWOM for newer products is of particular importance on e-commerce platforms ($\beta^e = .098$; $p < .05$; $\bar{r}^e = .147$) and for tangible products ($\beta^t = .136$; $p = .01$; $\bar{r}^t = .177$). Managers should pay particular attention to eWOM about products with higher financial risk ($\beta^o = .054$; $p < .05$; $\bar{r}^o_{low} = .012$; $\bar{r}^o_{high} = .119$), especially on e-commerce platforms ($\beta^e = .058$; $p < .10$; $\bar{r}^e_{low} = .055$; $\bar{r}^e_{high} = .112$) and for new products ($\beta^n = .091$; $p < .10$; $\bar{r}^n_{low} = .104$; $\bar{r}^n_{high} = .280$), though these effects are marginally significant.

eWOM metric amplifying effectiveness on sales: volume. The predicted correlations confirm a positive impact of the volume of eWOM on sales ($\bar{r}^o_{cum.volume} = .114$; $\bar{r}^o_{avg.volume} = .083$; $\bar{r}^o_{incr.volume} = .079$), providing supporting evidence for the bandwagon effect. A formal test of the overall volume and overall valence metrics lends further support to the conclusion that eWOM volume has a stronger impact on sales than eWOM valence (t-value = 5.59, $p < .001$). Our results overturn the finding of Floyd et al. (2014) and You, Vadakkepatt, and Joshi (2015) that volume is less effective than valence. We explain this difference in results by a combination of our conceptual and methodological choices. First, we offer a conceptualization of eWOM metrics that disentangles the often mixed-up effects of "valence only" and "valence plus volume," which are commonly labeled together as "valence." To empirically verify whether the difference is driven primarily by the more careful operationalization of the eWOM metrics, we incorporated our composite valence–volume metric into valence, as is more commonly done in the literature, and tested for differences between this confounded valence metric and volume. In this case, we no longer find a significant difference (t-value = –.04, $p = .964$, k = 1,430). This is an important finding because it illustrates that an incorrect classification of valence not only is conceptually wrong but also drastically changes empirical results and managerial recommendations.

The second difference between our results and those of the prior meta-analyses pertains to the use of different effect sizes (partial correlations vs. elasticities). In contrast with elasticities, our effect sizes are fully independent of measurement scale and more comparable across different metrics. Using effect sizes based on elasticities, we tested whether the stronger effect of valence over volume, as reported by Floyd et al. (2014) and You, Vadakkepatt, and Joshi (2015), would hold when a nonconfounded metric of valence is used. We find that using a confounded measure of valence leads to a higher effect of valence over volume, whereas with a nonconfounded valence metric, the difference between volume and valence disappears (t-value = –1.44, $p = .152$, k = 697), again highlighting the importance of separating our composite valence–volume metric from valence.

We find that cumulative volume is the most impactful metric for review platforms ($\bar{r}^r = .167$; $p < .0001$), utilitarian products ($\bar{r}^u = .169$; $p < .0001$), new products ($\bar{r}^n = .311$; $p < .0001$), and products with high financial risk ($\bar{r}^{hf} = .303$; $p < .01$). In many instances, cumulative volume exerts an impact on sales similar to that of incremental volume ($p > .10$): for e-commerce platforms ($\bar{r}^e_{cum.volume} = .173$; $\bar{r}^e_{incr.volume} = .147$), tangible products ($\bar{r}^t_{cum.volume} = .162$; $\bar{r}^t_{incr.volume} = .143$), services ($\bar{r}^s_{cum.volume} = .219$; $\bar{r}^s_{incr.volume} = .218$), mature products ($\bar{r}^m_{cum.volume} = .088$; $\bar{r}^m_{incr.volume} = .119$), and products with low financial risk ($\bar{r}^{lf}_{cum.volume} = .125$; $\bar{r}^{lf}_{incr.volume} = .129$).

Moreover, we identify platforms and products for which the effects of eWOM volume submetrics are not significantly different from the effects of composite valence–volume submetrics ($p > .10$): for social media ($\bar{r}^{sm}_{cum.volume} = .214$; $\bar{r}^{sm}_{pos.volume} = .167$), hedonic products ($\bar{r}^h_{incr.volume} = .256$; $\bar{r}^h_{pos.volume} = .284$), and mature products ($\bar{r}^m_{cum.volume} = .088$; $\bar{r}^m_{pos.volume} = .153$). This means that for these platforms and products, it is not only the mere volume of eWOM that counts most but also the combination of the bandwagon and persuasion dynamics represented by the amount of positive eWOM. In only one case (services) is positive valence as effective ($p > .10$) as cumulative volume and incremental volume ($\bar{r}^s_{cum.volume} = .219$; $\bar{r}^s_{incr.volume} = .218$; $\bar{r}^s_{pos.valence} = .198$).

Furthermore, we find that not all positive eWOM metrics are linked to an increase in sales ($\bar{r}^o_{pos.valence} = -.034$, $p > .10$; $\bar{r}^o_{pos.volume} = .107$, $p < .01$). Although previous studies have combined positive volume and positive valence into one metric, we find evidence that their effects are not identical and that positive volume is more strongly correlated with sales (the only exception identified in our sample is for services). The composite metric is an absolute number that effectively summarizes volume and valence at once by representing how many consumers expressed a positive (or negative) opinion about the product, whereas the valence metric expresses only consumers' relative sentiment about the product. Together with cumulative volume and incremental volume, positive volume is the most effective metric of eWOM. Table 6 provides an overview of the most important metrics per platform type and product characteristic.

eWOM metric attenuating effectiveness on sales: variability. The effects of negative eWOM are small and not significantly different from zero, which suggests that, on average, negative eWOM does not jeopardize sales ($\bar{r}^o_{neg.valence} = -.069$, $p = .938$; $\bar{r}^o_{neg.volume} = -.040$, $p = .789$). Negative valence hurts sales only in the later stages of the product life cycle ($\bar{r}^m = -.081$, $p < .05$) and for low-financial-risk products ($\bar{r}^{lf} = -.046$, $p < .05$). Our overall finding contrasts with You, Vadakkepatt, and Joshi's (2015) results. We argue that this may be due to the different samples in terms of products covered. Moreover, we are the first to demonstrate that large heterogeneity among consumers' product evaluations attenuates the effectiveness of eWOM, as shown by the negative correlation between variability and sales ($\bar{r}^o = -.163$, $p < .01$). When a product's evaluation is polarized, risk and uncertainty increase, thus leading consumers to avoid the product. This finding emerges also from the split-sample analyses for e-commerce platforms ($\bar{r}^e = -.125$, $p < .05$), tangible goods ($\bar{r}^t = -.133$, $p < .01$), utilitarian products ($\bar{r}^u = -.154$, $p < .001$), and products with high financial risk ($\bar{r}^{hf} = -.275$, $p < .05$). This finding is in line with the cue diagnosticity theory, which suggests that consumers rely less on eWOM when the variance of ratings is large because they may find the information nondiagnostic (Feldman and Lynch 1988; Li 2015).

Research methodology findings. Though not the main focus of our study, an important part of our meta-analysis

Table 6
IMPLICATIONS

A: For Platform Managers

	Implications for Social Media Platform Managers	*Implications for Review Platform Managers*	*Implications for E-Commerce Platform Managers*
eWOM is more effective for . . .	• Social media platforms with more sender homophily details		• E-commerce platforms with greater eWOM visibility • E-commerce platforms with less structured display of eWOM
	• Services		• New products
	• Cumulative volume, positive volume[a]	• Cumulative volume	• Cumulative volume, incremental volume[a] • High eWOM variability harms sales

B: For Product Managers

	Implications for Managers Based on Product Type		*Implications for Managers Based on Hedonic Score*		*Implications for Managers Based on Product Life Cycle Stage*		*Implications for Managers Based on Financial Risk*	
	Tangible	*Service*	*Hedonic*	*Utilitarian*	*New*	*Mature*	*High Financial Risk*	*Low Financial Risk*
eWOM is more effective for . . .	• Platforms with less structured display of eWOM			• Platforms with higher eWOM visibility • Platforms with less structured display of eWOM	• E-commerce platforms, review platforms • Platforms with more sender homophily details • Platforms with less structured display of eWOM	• Platforms with more sender trustworthiness details • Platforms with higher eWOM visibility	• Platforms with higher eWOM visibility • Platforms with higher eWOM posting costs	• Platforms with more sender homophily details
	• New products • Cumulative volume, incremental volume[a] • High variability harms sales	• Cumulative volume, incremental volume, positive valence[a]	• Positive volume, incremental volume[a]	• Cumulative volume • High variability harms sales	• Cumulative volume • High variability harms sales	• Cumulative volume, incremental volume, positive volume[a] • Negative valence harms sales	• Cumulative volume • High variability harms sales	• Incremental volume, positive volume, incremental variance[a] • Negative valence harms sales

[a]When multiple metrics are listed, they are not significantly different from each other.

Notes: This table is based on the HiLMA results on the split samples displayed in Table 5. Results displayed here are significant at $p < .05$ (two-sided). Cells are empty if no significant differences are found between platforms, products, or metrics.

involves investigating the moderating impact of research methodological choices on the relationship between eWOM and sales. We base our conclusions on the "Overall" column in Table 5 because the split-sample analyses do not allow us to draw generalizable conclusions about these methodological controls (Carney et al. 2011). We made several noteworthy discoveries. We find that failing to control for the effects of promotions leads to an overestimation of eWOM effectiveness ($\beta^o = -.040$; $p < .10$; $\bar{r}^o = -.016$). Not including the lagged term of the dependent variable in the response model ($\beta^o = -.067$; $p < .10$; $\bar{r}^o = -.038$) also leads to lower estimations of the effects of eWOM on sales. We also observe that accounting for endogeneity using first-difference models leads to lower estimates of the impact of eWOM ($\beta^o = -.118$; $p < .001$; $\bar{r}^o = -.066$), but using other types of endogeneity controls (e.g., simultaneous equations, instrumental variables) does not dampen the effectiveness of eWOM. Controlling for endogeneity varies across research streams, such that studies in marketing tend to correct for endogeneity more (66% of the marketing studies vs. 60% of economics and 57% of information technology studies). Whereas the most frequent endogeneity correction method in marketing and information technology is a first-difference approach, in economics it tends to be the use of instrumental variables. In a separate model, we explore interaction effects between these three research streams and endogeneity by using only one dummy variable for endogeneity controls to avoid multicollinearity. We find that, compared with studies from the marketing literature, the impact of eWOM is lower for economics studies ($\beta = -.141$, $p < .01$) and not significantly different for information technology studies ($\beta = -.052$, $p > .10$). After endogeneity has been accounted for, the effect of eWOM is higher for economics studies ($\beta = .349$, $p < .01$) and similar for both marketing and information technology studies ($\beta = .072$, $p > .10$) (see the Web Appendix). We observe that studies published in top-tier journals record a greater effect of eWOM on sales overall ($\beta^o = .072$; $p < .10$; $\bar{r}^o = .080$). Finally, we do not find significant differences for studies with higher precision of the effect sizes. This last result demonstrates the absence of publication bias (Stanley and Doucouliagos 2012).

DISCUSSION

In the last 15 years, many studies have advanced the understanding of the impact of eWOM. Overall, research has demonstrated that consumers use eWOM because it reduces their uncertainty and helps them choose the best offering, which affects the bottom line. However, prior studies have mostly relied on a single sample and thus have not been able to investigate platform- and product-related factors that moderate the effectiveness of eWOM. In addition, researchers have disagreed on which metric among the multiple eWOM metrics best captures this effect on sales. Although studies have attempted to synthesize earlier work (Floyd et al. 2014; You, Vadakkepatt, and Joshi 2015), the current study is the first to systematically examine the overall effect of consumer-generated information on sales across a large body of literature (96 studies)—covering 40 platforms, 26 product categories, and 11 countries, and spanning 15 years (1999–2013)—and to detail the differential effects of numerous operationalizations of eWOM (12 submetrics), all while considering various methodological designs. Our unique primary data collection through the Wayback Machine also enabled us to capture variation across platforms and products over time. Overall, we find a positive correlation of .091 between eWOM and sales. This finding implies that marketers should actively monitor eWOM, and it justifies the allocation of resources to eWOM management. Furthermore, this effect has not changed systematically in the last 15 years, which suggests that marketers should include eWOM in their long-term strategic decisions.

We set out to address two debates related to the contextual factors influencing the effectiveness of eWOM as well as to provide recommendations on methodological choices for further research. First, for which platform and product characteristics is eWOM more effective? In answering this question, we identify the characteristics of the platforms and their influence on eWOM effectiveness, thereby extending prior experimental findings (e.g., Berger and Iyengar 2013) and empirical work (e.g., Schweidel and Moe 2014) that highlights the role of channel characteristics in WOM communication. We find that the effectiveness of eWOM is not necessarily "symmetrical": that is, a product's eWOM may be more effective on a given platform, but for that very same platform, it may be that eWOM about other products leads to higher sales. This underscores the importance of specifying the perspective taken in academic studies (i.e., that of a platform manager [Table 6, Panel A] or that of a product manager [Table 6, Panel B]). Platform managers can influence the effectiveness of eWOM by accounting for the following two platform characteristics:

- To increase the effectiveness of eWOM spread on social media platforms, managers should encourage consumers to provide more information about themselves so that eWOM receivers can gauge homophily. This result is in line with a long line of research on tie strength and WOM persuasiveness in personal networks (e.g., Brown and Reingen 1987).
- For eWOM spread on e-commerce platforms, platform managers' efforts might focus on bringing eWOM information to the forefront without overstructuring it. Given an abundance of other product details available on this type of platform, it is crucial for eWOM to be prominent to have a strong impact on sales.

From the perspective of product managers who want to increase eWOM-driven sales, it is important to assess the most salient characteristics of their products (i.e., tangibility, hedonic score, stage in the product life cycle, and level of financial risk). With that in mind, Table 6 (Panel B) offers specific recommendations:

- For managers of tangible goods, platforms that display eWOM information in a less structured way host the most influential eWOM. In addition, eWOM about tangible goods is more effective in the early stages of the product life cycle when uncertainty is high and eWOM can be used to reduce functional risk.
- Managers of utilitarian products should keep in mind that eWOM is more effective on platforms where it is immediately visible and less structured.
- For new products, eWOM increases sales when it appears on e-commerce platforms and review platforms as well as on platforms with less structured display of eWOM, because these platform characteristics have been found to amplify the effectiveness of eWOM. Moreover, early in the product life cycle, consumers may be more concerned with whether they have something in common with the eWOM sender, potentially to reduce the risk of purchasing a product that does not fit their needs.
- For mature products, eWOM is more effective when appearing on platforms with greater eWOM visibility. In these later stages of the product life cycle, it becomes more important to assess whether the eWOM sender can be trusted. Because the product has been around for a while, there may be less uncertainty about its performance. However, uncertainty about the honest intentions of eWOM senders may increase over time because of the practices of review manipulation or fake-review spreading (Anderson and Simester 2014).
- For products with higher financial risk, eWOM has a stronger impact on the bottom line on platforms that display it more prominently or impose higher posting costs, whereas for products with lower financial risk, eWOM effectiveness is amplified on platforms with more homophily details.

These results imply that platform and product managers' perspectives may not be aligned, but they also highlight possible win-win scenarios. For example, we find a perfect match between e-commerce platforms and newly introduced products: eWOM on e-commerce platforms is especially effective for new products; for new products, in turn, eWOM displayed on e-commerce platforms is linked to the greatest impact on sales. In addition, we find that on e-commerce sites, it is eWOM's visibility and less structured display that increase effectiveness. These platform characteristics increase eWOM effectiveness also for utilitarian products, highlighting a mutual interest between e-commerce platform managers and utilitarian product managers. Similarly, we show that for social media platforms, eWOM effectiveness is particularly boosted when sender homophily details are provided. This is also the case for products with low financial risk. Thus, in these instances, platform and product managers' interests can be aligned, leading to a win-win situation for both parties.

The second debate addressed in this study centers on the following question: What are the differential effects of eWOM metrics on sales? In our research, we move beyond the simple comparison between volume and valence metrics (Floyd et al. 2014; You, Vadakkepatt, and Joshi 2015) to analyze four key metrics of eWOM. The composite valence–volume metric is a new measure that we introduce herein to better distinguish eWOM sentiment measured in absolute terms (e.g., total number of positive eWOM) from eWOM sentiment measured in relative terms (e.g., ratio of positive eWOM). One key contribution of our research is the insight that volume and composite valence–volume are the most important metrics linked to sales. This finding extends the theory of interpersonal influence and provides new insights into the relative importance of and interplay between the bandwagon and persuasion dynamics that underlie the link between eWOM and sales. In particular, we demonstrate the dominance of the bandwagon effect over the persuasion effect (with volume submetrics being more effective than valence submetrics) as the dynamic that best explains eWOM effectiveness. The persuasion effect is important, especially in combination with the bandwagon effect (as demonstrated by the large significant effect of the positive volume vs. positive valence submetric). Consequently, future studies should differentiate between composite valence–volume and valence to better represent how eWOM works in the marketplace. Failing to do so could result in an overestimation of the effectiveness of valence relative to that of volume.

We reconcile extant literature by demonstrating that negative eWOM is not linked to a decrease in sales, except for mature products and products with low financial risk (e.g., books, DVDs). The finding that positive eWOM metrics, overall, have a greater effect on sales than negative eWOM metrics underscores a positivity bias (Zhang, Craciun, and Shin 2010). This finding lends support to the notion that in the online context, favorable information produces greater effects than unfavorable information. This is in line with prior research demonstrating that consumers prefer and are more influenced by positive eWOM because they suspect that negative eWOM likely comes from a company's competitor (Ong 2011).

Another important contribution of our study is the insight that eWOM variability negatively affects sales. Neither of the two prior meta-analyses on eWOM effectiveness takes this metric into account, thus ignoring its influence on firm performance. We find that greater consumer consensus lowers functional risk, consequently boosting sales. In contrast, divergent opinions and polarized sentiment increase consumers' uncertainty about a product's performance and thus negatively affect the bottom line. Our results highlight the relevance of monitoring and managing heterogeneity among consumers' product evaluations, especially when eWOM is spread on e-commerce sites. Furthermore, the split-sample analyses indicate when variability may be less of a concern (i.e., for services, hedonic products, mature products, and products with low financial risk).

Finally, the present study offers important implications for researchers. First, the approach used to control for endogeneity can influence results. In line with Chintagunta, Gopinath, and Venkataraman (2010), the impact of eWOM does not change substantially when using instrumental variables or the generalized method-of-moments approach to control for endogeneity. However, the use of first-difference models can result in lower parameter estimates. Furthermore, we find that it is necessary to control for product prices and promotions, because leaving them out may lead to biased coefficients. We also find weaker effects of eWOM when the model includes the previous level of sales. Future models should avoid omitted variable bias, because a smaller number of parameters may lead to an overestimation of the effectiveness of eWOM.

LIMITATIONS AND DIRECTIONS FOR FURTHER RESEARCH

Meta-analyses have limitations as well as strengths. First, the factors we examine are constrained to variables for which sufficient primary data are available. Thus, our framework should be considered a summary of the most commonly studied contextual factors related to the eWOM environment, not an exhaustive list. Second, we could not investigate the role of eWOM senders' and receivers' characteristics, such as prior knowledge, product involvement, opinion leadership, and the stage in the consumer decision-making process, because doing so requires individual-level data. Third, we could only provide empirical generalizations about platforms and products covered in our sample. The majority of data points in our meta-analysis come from Amazon.com and relate to books and movies. These platforms and product categories were obvious first choices to examine the phenomenon of eWOM because data are easily accessible. However, we encourage researchers to enlarge the scope of eWOM research in terms of platforms and product categories. Similarly, most studies on eWOM "use a narrow set of metrics such as numerical ratings or volume, ignoring the information content of text in these reviews, which is rich in consumer expressions" (Tirunillai and Tellis 2012, p. 199). Consequently, we suggest that researchers consider different eWOM operationalizations that capture formats other than textual posts and ratings (e.g., "pins," images, videos, audio recordings). These other formats may require more initial qualitative work to set the ground for future quantitative analysis. In general, more attention should be devoted to the analysis of the content of eWOM, which so far has been fairly limited. Fourth, we encourage scholars to use multiple eWOM measures to capture the different aspects of eWOM, as one measure alone cannot fully depict such a heterogeneous and complex variable. Fifth, more insight is necessary into the way consumers respond to eWOM that they have actually read, seen, or heard versus eWOM that was merely present on the platform but was never received. Sixth, we recognize the lack of empirical studies investigating the effect of external eWOM (i.e., eWOM about a competing product, brand, or firm). Additional research is warranted in this area.

In conclusion, this article makes important contributions to the understanding of the impact of eWOM on sales and the factors influencing this relationship. We find that the effectiveness of eWOM is dependent on both the online environment in which it is displayed and the product to which it pertains. This means that additional eWOM research should account for the context of eWOM and that managers should differentiate their eWOM strategies according to the particular platforms and products. Finally, it is important to monitor and measure multiple eWOM metrics while paying particular attention to volume and variability.

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