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# Searching for word of mouth in the digital age: Determinants of consumers' uses of face-to-face information, internet opinion sites, and social media

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A R T I C L E I N F O

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A B S T R A C T

In the digital era, consumers choose among various types of word of mouth (WOM) when searching for product information. This research investigates how consumers allocate their search efforts across three key WOM types: face-to-face (e.g., offline communication among consumers), Internet opinion sites (e.g., product reviews), and social media platforms (e.g., recommendations on Facebook). The authors develop a conceptual framework of WOM types and derive hypotheses about the determinants of WOM search behaviors, which they test against representative data from more than 2,000 consumers. Several product and consumer characteristics have systematic effects on search effort allocation, as do WOM type–specific resources. A process-related analysis also suggests different roles of WOM types during customers' search journeys, such that face-to-face conversations and Internet opinion sites tend to be consulted early, whereas social media mostly serve as final information sources. Overall, the results caution against assuming that the different WOM types are arbitrary or random substitutes.

## 1. Introduction

Word of mouth (WOM) is one of the most influential information sources for consumers (Brown & Reingen, 1987; Katz & Lazarsfeld, 1955). In addition to receiving information through face-to-face interactions with others, consumers in the digital age can learn from product reviews on Internet opinion sites (e.g., Amazon, Yelp, Trustpilot) or social media (e.g., Facebook, Twitter). Because these platforms and the forms of WOM they produce differ vastly, in terms of personal connections, synchronicity, and feedback options, a deeper understanding of the functions of various types of WOM for consumers is demanded, beyond imposing a simple online–offline dichotomy (Berger & Iyengar, 2013; Hennig-Thurau et al., 2015; Lovett et al., 2013).

While research has shed light on each WOM type individually (e.g., face-to-face, de Matos & Rossi, 2008; Internet opinion sites, You et al., 2015; social media, Hennig-Thurau et al., 2015), limited insights exists into how the differences manifested by various WOM types influence consumers' WOM usage, particularly over the course of their search process (cf. Berger & Iyengar, 2013; Rosario et al., 2020). Notable exceptions include Eisingerich et al. (2015) and Eelen et al. (2017) who point at fundamental conceptual differences among WOM types, and Marchand et al. (2017) who provide evidence that the impact of WOM on Twitter and Amazon varies before versus after a product's launch. But many more questions remain regarding why and how consumers use WOM types while undertaking their search journey.

This article reports on a systematic analysis of factors that might explain how consumers allocate their search activities across WOM types when seeking purchase-related product information, in total and in each stage of the search journey. Our proposed conceptual framework, situated in extant literature, anticipates key differences among the three WOM types. On the basis of this framework, we derive hypotheses about which factors might explain differences in search behaviors across WOM types, which we categorize as product characteristics, consumer characteristics, and WOM type–specific resources. With a representative data set pertaining to the stated WOM search behaviors of more than 2,000 consumers and multivariate fractional regression analysis, we establish evidence of some substantial differences in consumers' uses of WOM types, with systematic effects for all three sets of characteristics. In a process-related follow-up analysis we then identify when consumers turn to the different WOM types during their search journeys. We find that face-to-face conversations and Internet opinion sites tend to be consulted early, whereas social media platforms mostly serve as final information sources.

This research thus provides scholars and managers with a deeper

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understanding of consumers' search behavior in the digital era. It offers an initial delineation of the conditions in which consumers consult a certain type of WOM in their search for information, and it reveals the points in consumers' search journeys when consumers likely consider each WOM type. These insights can help managers fine-tune their monitoring and efforts to influence consumers' decision-making.

In the following, we first provide a literature overview about the differences among WOM types and how they relate to consumers' information search behavior. Second, we derive hypotheses, which we then test in an empirical investigation and third, we give insides into consumers' search journey and discuss our findings and contributions to managerial practice and the academic literature.

## 2. What we know (and don't) about different wom types

Table 1 summarizes the two main research streams on which we build our framework and hypotheses: studies that identify differences among WOM types, and research that investigates the determinants of WOM-related search behaviors.

### 2.1. Differences among WOM types

Several scholars have stressed the need to understand differences among WOM types (Berger & Iyengar, 2013; Dellarocas, 2003; Eelen et al., 2017; Eisingerich et al., 2015; Godes & Mayzlin, 2004; Hennig-Thurau et al., 2015; Meuter et al., 2013), as a response to the critical role of the communication channel (e.g., personal communication, opinion sites, social media) "in moderating the functions of word of mouth" (Berger, 2014, p. 601).

Hennig-Thurau et al. (2015) suggest a conceptual framework of WOM channel differences, and Berger (2014) describes how the communication channel can shape WOM. Empirical findings indicate that social and functional motives determine WOM articulation on social media platforms (SM WOM), whereas emotional motives are more prominent for f2f WOM (Lovett et al., 2013). WOM articulations on opinion sites are found to be less personal in character and more driven by internal consumer motives, whereas f2f WOM is motivated by external factors such as evaluative dissonance (Shin et al., 2014).

Noting the social character of SM WOM, Berger and Iyengar (2013) show that written communication, an essential element of all digital WOM, leads consumers to mention more interesting products and brands than does oral, in-person f2f WOM communication. Consistent with these results, Eisingerich et al. (2015) find that perceived social risk restricts SM WOM articulation (versus f2f WOM), whereas self-enhancement needs stimulate it. Eelen et al. (2017) also find that consumers express less brand loyalty on platforms (SM and IOS) than through f2f WOM, but their SM WOM and IOS WOM engagement increases if consumers want to help the brand or have high self–brand connections. Finally, differences in WOM depend on whether consumers use desktop platforms versus smartphones to express it (Lurie et al., 2014).

Other scholars investigate how WOM types differently influence consumer information sharing and product success. A qualitative study by Brown et al. (2007) establishes that the flow of WOM in online networks differs from that in offline contexts, and Baker et al.'s (2016) quantitative analysis of offline (f2f) and online (SM) WOM conversations finds f2f WOM to be more strongly associated with retransmission intentions, whereas they report the link between valence and purchase intentions to be stronger for SM WOM. For video games, Marchand et al. (2017) discover that Twitter volume (SM WOM) affects sales, though its influence declines with longer product availability, whereas Amazon review volume (IOS WOM) exerts greater impacts over time.

### 2.2. WOM and information search behavior

Behavioral research into the effects of WOM on *information search* focuses almost exclusively on single types of WOM. For example, Duhan et al. (1997) investigate factors that enable consumers to use f2f WOM

**Table 1**
Key Studies On WOM Types and WOM Search.

| | Differences between WOM Types | | | Determinants of WOM Search | | | Study Design | |
|---|---|---|---|---|---|---|---|---|
| Authors | Online vs. Offline | Different Types of Online | Other Types | Face-to-Face | IOS | SM | Empirical | Conceptual |
| *WOM type studies* | | | | | | | | |
| Hennig-Thurau et al. (2015) | x | x | | | | | | x |
| Berger (2014) | x | | | x | x | | | x |
| Lovett et al. (2013) | x | | | | | | x | |
| Shin et al. (2014) | x | | | | | | x | |
| Berger & Iyengar (2013) | x | | | | | | x | |
| Eisingerich et al. (2015) | x | | | | | | x | |
| Eelen et al. (2017) | x | | | | | | x | |
| Lurie et al. (2014) | | | x* | | | | x | |
| Brown et al. (2007) | x | | | | | | x | |
| Baker et al. (2016) | x | | | | | | x | |
| Marchand et al. (2017) | | x | | | | | x | |
| *WOM search studies* | | | | | | | | |
| Duhan et al. (1997) | | | | x | | | x | |
| Hennig-Thurau et al. (2003) | | | | | x | | x | |
| Chen & Berger (2016) | | | | | | | x | |
| Kasabov (2016) | | | | | | x | x | |
| Klein & Ford (2003) | | | | x | x | | x | |
| Beatty & Smith (1987) | | | | x | | | x | |
| Cheng & Ho (2015) | | | | | | | | |
| Claxton et al. (1974) | | | | x | | | x | |
| Moorthy et al. (1997) | | | | x | | | x | |
| Price & Feick (1984) | | | | x | | | x | |
| Punj & Staelin (1983) | | | | x | | | x | |
| Ratchford et al. (2007) | | | | x | x | | x | |
| Schmidt & Spreng (1996) | | | | x | | | | x |
| Srinivasan & Ratchford (1991) | | | | | | | | |
| Wang et al. (2012) | | | | | | x | x | |
| **This study** | x | x | x | x | x | x | x | |

Note: * Mobile vs. desktop WOM. Studies are listed in the order as they are mentioned in the literature review.

when searching for information, and Hennig-Thurau and Walsh (2003) study the motivational drivers for reading IOS WOM. According to Chen and Berger (2016), consumers' usage of SM WOM differs, depending on whether they are receiving content or actively searching for it. Kasabov (2016) also analyzes which motives and source characteristics lead consumers to seek SM WOM. As a notable exception to this trend, Klein and Ford (2003) provide evidence that forum chats (an early type of SM WOM) and f2f WOM searches are distinct activities, though they do not attempt to explain their usage determinants, which is the focal objective for our research.

Based on this review, we concur with Berger's (2014, p. 601) assertion, in relation to WOM types, that "much more work remains to be done, and this is an open area for further investigation," and we propose that this argument particularly applies to consumers' uses of WOM in their search efforts. Rosario et al. (2020) also emphasize the need for greater insights into search-related activities. In response, we seek to identify key determinants of how consumers allocate their search activities across different WOM types and their potentially distinct influences throughout consumers' decision-making journeys.

## 3. Conceptual framework and hypotheses

The structural differences among WOM types offer the foundation for predicting how consumers allocate their efforts to search for product-related information across WOM types. Hennig-Thurau et al. (2015) identify unique characteristics of WOM on social media platforms, distinct from other WOM types, and we leverage their work to build our conceptual framework in Fig. 1, which indicates key structural differences across face-to-face WOM (f2f), WOM on Internet opinion sites (IOS), and WOM on social media platforms (SM).

In our framework, WOM types differ with regard to (1) their digital nature, such that IOS and SM WOM are online but f2f WOM is offline; (2) the connections between sender and receiver, whether personal for f2f WOM and SM WOM or impersonal for IOS WOM; (3) their communication mode, namely, synchronous (f2f WOM and SM WOM) versus asynchronous (IOS WOM); (4) their communication styles, which could be one-to-one as in f2f WOM, one-to-many as in IOS WOM, or many-to-many as in SM WOM; (5) the length of the messages shared, which tend to be long for f2f WOM and IOS WOM but limited for SM WOM; and (6) their time relatedness, whether time independent like IOS WOM and SM WOM or time dependent/instant like f2f WOM.

We also leverage the insights of a detailed literature review by Maity et al. (2014), related to online information searches, to argue that these conceptual differences influence the value that each WOM type offers to consumers searching for product-related information in a particular situation. As a result, we argue that the value of any particular WOM type as a source of information varies with the characteristics of the product for which the consumer needs information, his or her own general characteristics, and the consumer's specific resources pertaining to each WOM type. These value differences will result in differences in consumers' uses of each WOM type when searching for information. We therefore offer hypotheses about how each category of characteristics influences consumer search activities.

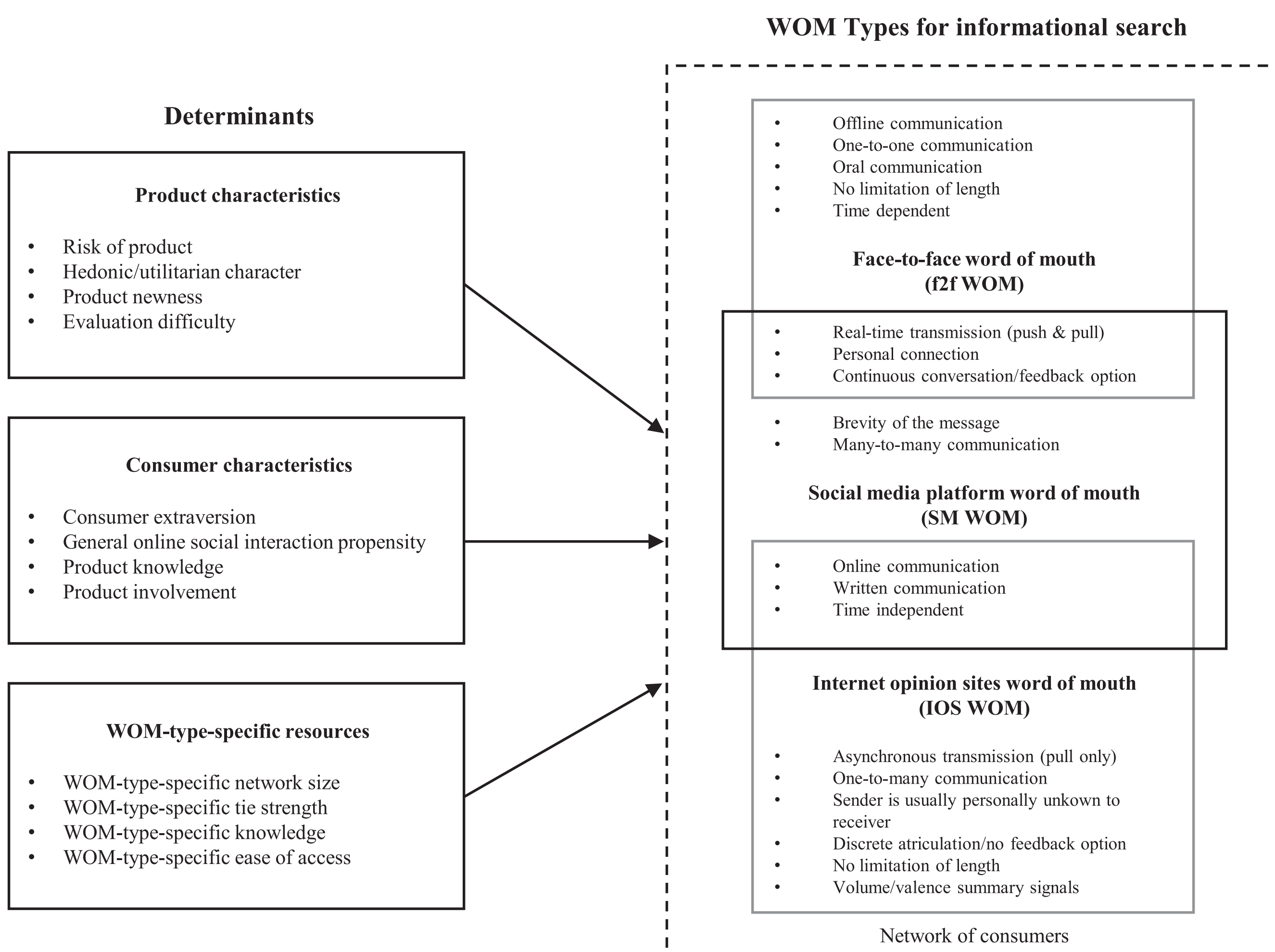


**Fig. 1.** Contingency Framework of WOM Types for Information Search.

### 3.1. Product characteristics and WOM type usage

*Product risk*. Most purchase decisions involve some degree of uncertainty, and searching for product information is a crucial means to reduce the associated risk that such uncertainty creates (Beatty & Smith, 1987; Schmidt & Spreng, 1996). We define product risk as consumers' sense of uncertainty regarding the chances they will suffer negative consequences (financial, social, psychological, security-, time-related) if they buy a specific product (Dowling & Staelin, 1994, p. 125). Because WOM types might reduce risk to varying degrees, their uses could depend on consumers' risk perceptions. For example, f2f WOM is unlimited in length, so it allows consumers to engage in rich conversations, but it also is limited to one-to-one communication, which restricts the number of sources from whom the consumer can gather information. The chances that any particular consumer's f2f WOM connections are experts in a specific consumption context tend to be small on average, so the ability of f2f WOM to reduce the focal consumer's risk concerns might be lower (Cheng & Ho, 2015), relative to other WOM types that may offer wider access to experts in a specific field.

A similar limitation might apply to SM WOM, though for different reasons. Whereas SM WOM's many-to-many communication provides access to many other sources of information (i.e., offers greater potential to find experts), its length limitations—whether imposed by the platform (e.g., Twitter) or resulting from the inconvenience of typing on smartphones (Lurie et al., 2014)—likely impede the transmission of detailed, rich product information.

In contrast, IOS WOM grants consumers access to extensive and rich information, often including several reviews about a single product, potentially written by experts, detailing the strengths and weaknesses of the product. Review length rarely is limited. Moreover, valence and volume signals (e.g., average star ratings) are available from most IOS WOM platforms (e.g., Amazon), so consumers have an easy means to process and aggregate various perspectives. Accordingly, this type of WOM should be particularly effective for reducing purchase risk.

**$H_1$**: The perceived risk of a product has (a) a negative effect on the share of WOM information search that the consumer allocates to f2f WOM, (b) a negative effect on the share of WOM information search that the consumer allocates to SM WOM, and (c) a positive effect on the share of WOM information search that the consumer allocates to IOS WOM.

*Utilitarian/hedonic character*. Utilitarian products, characterized as functional and useful (Holbrook & Hirschman, 1982), are less often topics discussed during interpersonal interactions among consumers (Dhar & Wertenbroch, 2000). People prefer to talk about interesting products, and interestingness, fun, and excitement tend to be associated with hedonic products, such as movies or smartphones (Berger & Schwartz, 2011; Chung & Darke 2006). This "interestingness effect" might influence both giving and searching for information through WOM, when the search activity involves personal interactions among peers. Therefore, we argue that a product's hedonic appeal and its associated interestingness level may lead consumers to use WOM types that involve more personal connections (i.e., f2f WOM and SM WOM) when searching for information. If a product is predominantly utilitarian though, consumers might prefer IOS WOM for their search, because it does not involve (undesired) personal connections.

**$H_2$**: The utilitarian character of a product has (a) a negative effect on the share of information search that a consumer allocates to f2f WOM, (b) a negative effect on the share of information search that a consumer allocates to SM WOM, and (c) a positive effect on the share of information search that a consumer allocates to IOS WOM.

*Product newness*. If a product has been introduced only recently, which we use as a measure of product newness (Kleinschmidt & Cooper, 1991), diffusion theory predicts that relatively few consumers (i.e., innovators, Rogers, 2003) will have experienced it already. In this case, the one-to-one communication style of f2f WOM, in combination with the strong personal connections that mark it (Duhan et al., 1997), may limit the probability that consumers can access innovators, because they might not know them personally. But the many-to-many and one-to-many communication styles of SM WOM and IOS WOM should help searchers access reviews of new products by innovators. Because personal ties tend to be weaker (SM WOM) or nonexistent (IOS WOM) for these digital WOM types, information also flows more readily across different consumer groups, such as from innovators to later adopters (Brown & Reingen, 1987). Of these two digital WOM types, we anticipate that the suitability of SM WOM for information about newly released products is even greater, due to its real-time nature and "push" character (Hennig-Thurau et al., 2015). Thus, we predict that product newness encourages the use of the digital types, IOS WOM and SM WOM, over f2f WOM.

**$H_3$**: Product newness has (a) a negative effect on the share of information search that a consumer allocates to f2f WOM, (b) a positive effect on the share of information search that a consumer allocates to SM WOM, and (c) a positive effect on the share of information search that a consumer allocates to IOS WOM.

*Evaluation difficulty*. A consumer's decision to search for information using a specific WOM type also depends on the difficulty of the evaluation task (Claxton et al., 1974; Laroche et al., 2005). We define evaluation difficulty as "consumers' perceptions of the cognitive and behavioral difficulty and effort required to judge and discriminate among alternatives, and make a selection decision" (Laroche et al., 2005, p. 253). Because the communication modalities (many-to-many, one-to-many) of SM WOM and IOS WOM offer greater access to the "wisdom of the crowd" (Surowiecki, 2005), consumers likely turn to them, rather than to f2f WOM, to make especially difficult decisions. The two digital WOM types aggregate and provide the opinions of many *different* consumers; reading reviews or postings by this dispersed group of other consumers should help the focal consumer gather various perspectives on a choice problem and reduce decision difficulty better than input from selected f2f WOM peers. In addition, because both digital WOM types are based on written communication, the information is stored and can be reviewed if needed (i.e., time independent). The consumer can come back and reassess the information or combine it with other sources, which may be especially helpful when it is difficult to evaluate a product. However, we have no strong rationale for predicting which of the digital WOM types appeals most to consumers faced with a difficult evaluation task. Whereas IOS WOM provides summary signals that reduce complexity, SM WOM enables interactivity, such that the consumer can discuss complex questions with his or her social network.

**$H_4$**: Evaluation difficulty has (a) a negative effect on the share of information search that a consumer dedicates to f2f WOM, (b) a positive effect on the share of information search that a consumer dedicates to SM WOM, and (c) a positive effect on the share of information search that a consumer dedicates to IOS WOM.

### 3.2. Consumer characteristics

*Extraversion*. Extraversion implies an orientation toward external and social interactions, such that it tends to be associated with behaviors such as being sociable, gregarious, and talkative (Barrick & Mount, 1991; McCrae & John, 1992). Because f2f WOM offers consumers a good means to express themselves and interact in traditional, personal ways (Landers & Lounsbury, 2006), we expect that extraverted consumers are more likely to search for product information through f2f WOM. In contrast, IOS WOM does not support personal connections between senders and receivers and offers no room for personal interactions or feedback, so extraverted consumers may tend to avoid this WOM type. Whereas SM WOM offers interaction opportunities for consumers, at least in written form, these personal interactions differ fundamentally from offline, face-to-face interactions (Blazevic et al., 2014). Social media, compared with f2f WOM, offer relatively limited potential for extraverted consumers to express themselves, so we expect a greater share of searches for f2f WOM than for digital alternatives among extraverted consumers.

**$H_5$**: Consumer extraversion has (a) a positive effect on the share of information search that a consumer allocates to f2f WOM, (b) a negative effect on the share of information search that a consumer allocates to SM WOM, and (c) a negative effect on the share of information search that a consumer allocates to IOS WOM.

*General online social interaction propensity*. Consumers' general online social interaction propensity (GOSIP) is a "trait-based individual difference that captures the differences between consumers in their predisposition to interact with others in an online environment" (Blazevic et al., 2014, p. 87). It parallels extraversion, except in the digital realm. Consumers with a high propensity prefer online environments, so offline f2f WOM is less attractive for such consumers, and they likely avoid searching for information offline. In contrast, SM WOM is ideal, because consumers can act out their propensity for online social interaction through easy interactions with friends and followers, enhanced by this WOM type's real-time transmission and push character (Hennig-Thurau et al., 2015). The effect of GOSIP on IOS WOM search is less clear though. Despite its online nature, IOS WOM offers limited space for active articulation or interactions. Considering the importance of interactions for people with high GOSIP, we cautiously predict a negative effect on IOS WOM as well.

**$H_6$**: General online social interaction propensity has (a) a negative effect on the share of information search that a consumer allocates to f2f WOM, (b) a positive effect on the share of information search that a consumer allocates to SM WOM, and (c) a negative effect on the share of information search that a consumer allocates to IOS WOM.

*Product knowledge*. Subjective product knowledge, or what the consumer thinks she or he knows about a product, can limit or increase search activities, "by allowing consumers to have a richer understanding of what they are evaluating" (Srinivasan & Ratchford, 1991, p. 234; see also Moorthy et al., 1997). The *kind* of information that consumers seek also should differ with their knowledge (Maity et al., 2014), in that consumers with more knowledge might search for more detailed, differentiated information, whereas those with little knowledge about a product may be more interested in basic, general information. The three WOM types address these distinct informational needs to varying degrees, so we posit that consumers' product knowledge influences their uses.

Specifically, consumers who already possess substantial product knowledge but are searching for more might consider using f2f WOM, because its feedback options and potentially unlimited length provide access to rich information. However, its one-to-one communication style limits the likely availability of "true" product experts. In this sense, f2f WOM likely cannot function as a powerful forum for exchanging complex and controversial perspectives among experts, so we expect a negative effect. We also expect a negative effect of greater product knowledge on the use of SM WOM, though for different reasons. In this case, the digital social network probably provides a broad range of product-related information, but the brevity of the exchanged messages might minimize the potential to share detailed product information or substantially increase knowledge among those who already consider themselves experts. Finally, IOS WOM provides consumers with access to a plethora of reviews by heterogeneous others, including experts, often without any limitations on review length, which supports detailed articulations. The reviews also remain stored and can be reread if needed. Thus, we expect it to be the prime WOM type used by consumers who seek to extend their already strong knowledge about a product or category.

**$H_7$**: The level of a consumer's product knowledge has (a) a negative effect on the share of information search that a consumer allocates to f2f WOM, (b) a negative effect on the share of information search that a consumer allocates to SM WOM, and (c) a positive effect on the share of information search that a consumer allocates to IOS WOM.

*Product involvement*. Involvement, defined as the "perceived relevance of the object based on inherent needs, values, and interests" (Zaichkowsky, 1985, p. 342), affects information search, because consumers with greater involvement in a product category tend to seek exhaustive product information. The search process is not just a means to an end; it is a rewarding activity in itself (Rothschild, 1984). The WOM types address the search-related needs of high involvement consumers to varying degrees, so their WOM type usage should vary as well.

In particular, IOS WOM offers highly involved consumers various ways to satisfy their informational needs, despite its lack of interaction potential. Forums and platforms publish detailed reviews by different consumers, which are fun to browse and easily accessible. Some WOM sources on such platforms are category enthusiasts too (Kozinets, 2002), who also express their high involvement. The different stored reviews form a "library" that can support extensive product research should be particularly attractive for highly involved consumers. In contrast, f2f WOM and SM WOM may be less appealing for highly involved consumers. The amount of information and number of category enthusiasts both are restricted in f2f WOM, as a result of its one-to-one character. The insights and pleasure a highly involved consumer gains from SM WOM also may be limited by the enforced message brevity.

**$H_8$**: The level of a consumer's product involvement has (a) a negative effect on the share of information search that a consumer dedicates to f2f WOM, (b) a negative effect on the share of information search that a consumer dedicates to SM WOM, and (c) a positive effect on the share of information search that a consumer dedicates to IOS WOM.

### *3.3. Consumers' WOM type–specific resources*

Consumers select information sources in an effort to maximize their welfare and minimize their search costs (Ratchford et al., 2001). Drawing on this general argument, we posit that WOM type usage is also a function of the resources a consumer possesses for each WOM type; more WOM type–specific resources should increase type usage to search for information. Specifically, we propose that four type-specific resources determine consumers' WOM type choice: knowledge, network size, tie strength, and ease of access. Paralleling our arguments for product and consumer characteristics, we anticipate that consumers' WOM type choice depends on their *relative* type-specific resources, rather than absolute resources.

*WOM type–specific knowledge*. We define a consumer's WOM type–specific knowledge as the subjective knowledge that a consumer has about a specific WOM type. Considering their varying novelty and technological requirements, this knowledge should differ substantially across WOM types. Consistent with a general cost–benefit approach, we argue that the more knowledge a consumer has about a specific WOM type (relative to other WOM types), the more search activities the consumer is likely to conduct through that specific type (Punji & Staelin, 1983).

**$H_{9a}$**: The greater a consumer's knowledge regarding a specific WOM type, relative to other WOM types, the greater the share of information search that the consumer dedicates to this WOM type.

*WOM type–specific network size*. For this research, we define a consumer's WOM type–specific network size as the number of contacts a consumer has to support a certain WOM type. For f2f WOM and SM WOM, these contacts are people the consumer knows and can obtain information from, regarding the product in question. The number of websites offering product reviews represents our measure of IOS WOM type–specific network contacts. Network sizes differ substantially; for example, SM WOM networks range from just a few friends or followers to thousands of them. Similar differences in size also likely exist in relation to purchase-related networks, such as the number of friends a consumer considers experts in the product category. Again, a greater (relative) network size for a specific WOM type should shift consumers' search activities toward that type.

**$H_{9b}$**: The greater a consumer's network size for a specific WOM type relative to other WOM types, the greater the share of information search that the consumer dedicates to this WOM type.

*WOM type–specific tie strength*. Building on the general notion of tie strength (Granovetter, 1973), we define WOM type–specific tie strength as the closeness expressed between the receiver of information shared through a particular WOM type and the sender of that information, as perceived by the receiver. It should vary among consumers; for some people, the SM WOM network consists of close personal friends, but others only know their Facebook friends very superficially. Despite the generally impersonal character of IOS WOM, perceived tie strength differs, because some consumers sense greater closeness to authors of online reviews (e.g., film fans reading reviews on a movie site written by other film fans). Because tie strength is associated with positive valuations, such as trust and reliability, and strong ties generally are preferred over weak ones (Bansal & Voyer, 2000), we argue that greater tie strength in a specific WOM type (relative to other WOM types) leads consumers to use this type more (Wang et al., 2012).

**$H_{9c}$**: The stronger a consumer's ties for a specific WOM type relative to other WOM types, the greater the share of information search that the consumer dedicates to this WOM type.

*WOM type–specific ease of access*. The final WOM type–specific resource we consider refers to consumers' perception that it is easy to gather product-related information from a specific WOM type. Access to high-speed Internet which is free from interference is dispersed across consumers (e.g., those living in the countryside vs. big cities), so the ease of access to SM WOM and IOS WOM should vary. Also, consumers living in more central or populated parts of a country might have easier access to f2f WOM than those in rural parts. Building on a general cost–benefit logic, we anticipate that greater ease of access to a WOM type reduces search costs and thus increases that type's relative usage by consumers (Price & Feick, 1984).

**$H_{9d}$**: The more easily a consumer can access a specific WOM type, relative to other WOM types, the greater the share of information search that the consumer dedicates to this WOM type.

## 4. Hypotheses testing

### 4.1. Method and sample

We conducted a large-scale online survey to test our hypotheses. To rule out trivial insights (e.g., people do not search for WOM on social media platforms because they do not use social media), we sought a sample of consumers who could *potentially* use all three WOM types. Face-to-face interactions occur naturally in everyone's lives, and the online nature of the survey ensured that all respondents had access to the Internet and could visit opinion platforms. Social media usage, however, required particular attention. To ensure that all respondents could also use SM WOM as part of their search process, we only included consumers who were active members of Facebook or Twitter, the two most widely used social media networks during the time of our data collection.

Kantar Lightspeed GMI, a professional market research firm applied quota sampling, according to available demographic information about its database members, to identify and solicit the participation of survey respondents who were representative of the wider population of social media users in Germany in terms of age, gender, and education (see Appendix A for more details). Of the 2,502 respondents who met basic screening criteria and received the main survey, 2,039 completed the survey without quality issues and entered the final sample. However, 463 participants were deleted (18.5%) from the final sample due to quality issues (i.e., too fast = 194 [7.8%], answered every question the same way = 15 [0.6%], answered the quality checks wrong = 254 [10.15%]). The average age of respondents in the final sample was 35.4 years (SD = 12.7), and 50.9% were women.

The respondents received a list of product categories (including services) and indicated in which categories they had recently (i.e., within the previous three months) purchased a product for which they had consulted at least one type of WOM about the product or alternative options. The product list spanned a wide range, from daily needs (e.g., groceries, beauty products) to media (e.g., books, movies, games) and recreational services (e.g., hotels, restaurants). If a respondent noted several purchases for which he or she had consulted WOM, we allocated the response to the category with the fewest respondents, so that we could achieve a more balanced distribution across product categories.

With this approach, we can use stated behaviors as the basis for our analysis. Although such behavioral data can be affected by subjective consumer memories and evoke recall biases (Kuusela & Paul, 2000), it also captures actual purchase-related *behaviors* and thus help to avoid the validity problems often associated with hypothetical consumption, consumer intentions, perceptual measures, or generic judgments (Chandon et al., 2005). In addition, because respondents had to indicate various aspects of the decision-making process they underwent before making the concrete purchase, they should be more likely to recall the details and corresponding circumstances, which might lower a potential recall bias (Kuusela & Paul, 2000), even if we cannot eliminate it completely. Finally, the three-month time window, within participants had to remember the focal product purchase, has been identified as efficient for reducing potential recall bias in other research areas (Kjellsson et al., 2014).

In the survey itself, after describing the details of the purchase, respondents indicated the extent to which they used the different WOM types, then answered several questions about their consumer characteristics. The survey ended with items designed to measure each respondent's WOM type–specific resources.

### 4.2. Measures

We report all measures and items in Table 2. For WOM type usage, we assessed the extent to which a respondent used a specific WOM type in preparation for the purchase, on a seven-point scale (1 = "I did not use this type to obtain information before I bought the product," 7 = "I used this type intensively to obtain information before I bought the product"). To account for potential differences between the most prominent social media networks, we measured SM WOM usage and all corresponding items (i.e., WOM type–specific resources) at the network level. That is, we gathered separate measures for Facebook and Twitter, but the SM WOM usage item in the analyses indicates the maximum value of Facebook and Twitter usage.[1] Reflecting our interest in the *relative* usage of a WOM type (i.e., one type's usage relative to the usage of other WOM types), we divided the absolute usage value for each WOM type by the sum of the usage scores for all three WOM types.

Seven-point scales measure the various determinants of consumers' WOM type usage as well. Regarding product characteristics, we measured product risk with three items from Jain and Srinivasan (1990); we assessed the utilitarian/hedonic character of a product with three items from Voss et al. (2003). For perceived product newness, we used a single item that asked respondents how long they thought the product had been available on the market when they purchased it (1 = "available for a long time," 7 = "brand new to the market"). We measured evaluation difficulty with two items from Laroche and colleagues (2005).

For the consumer characteristics, we employed three items to measure consumer extraversion, which we took from the Big Five inventory (McCrae & John, 1992). Our measure of online social interaction propensity consisted of four items from Blazevic et al. (2014). For product knowledge, we applied the single-item approach advocated by Brucks (1985) (1 = "I knew nothing about the product," 7 = "I knew a lot about

[1] We reran all regression analyses with network-specific measures. Although a few significance levels differ, the z-tests of parameter differences between models indicate no significant differences in Facebook and Twitter usage for *any* determinants (p-values ranging between 0.834 and 0.163). The two networks' roles thus appear to be influenced in similar ways by product and consumer characteristics and WOM type–specific resources. We report the network-specific results in Appendix B for comparison purposes.

**Table 2**
Measures.

| Construct | Items | Cronbach's Alpha (Product/Service) | McDonald's Omega (Product/Service) | AVE (Product/ Service) | Source |
|---|---|---|---|---|---|
| *Product characteristics* | | | | | |
| Risk of product[a] | 1. It is really annoying to make an unsuitable purchase regarding this kind of product.<br>2. It would be upsetting to make a poor choice regarding this kind of product.<br>3. One can lose a lot by making a poor choice regarding this kind of product. | 0.87/0.84 | 0.87/0.85 | 0.70/0.66 | Jain & Srinivasan (1990) |
| Utilitarian/hedonic character[a] | 1. This kind of product is generally functional.<br>2. This kind of product is generally necessary.<br>3. This kind of product is generally practical. | 0.83/0.84 | 0.82/0.83 | 0.62/0.64 | Voss et al. (2003) |
| Product newness[b] | 1. The product was available on the market. | N.A. | N.A. | N.A. | New scale |
| Evaluation difficulty[a] | 1. The decision to buy the product was very difficult.<br>2. The decision to buy the product was very complex. | 0.82/0.84 | N.A. | 0.69/0.74 | Laroche et al. (2005) |
| *Consumer characteristics* | | | | | |
| Consumer extraversion[a] | 1. I am talkative and like to talk to other people.<br>2. I am enthusiastic and easily carry other people along.<br>3. I can let myself go and I am sociable. | 0.90/0.88 | 0.90/0.88 | 0.76/0.71 | McCrae & John (1992) |
| GOSIP[a] | 1. In general, I am someone who answers questions of others in online discussion forums.<br>2. In general, I am someone who enjoys initiating a dialog online.<br>3. I am someone who likes actively participating in online discussions.<br>4. In general, I thoroughly enjoy exchanging ideas with other people online. | 0.94/0.94 | 0.94/0.94 | 0.78/0.79 | Blazevic et al. (2014) |
| Product knowledge[c] | Rate your knowledge of the product (name)—before you received information from other consumers—as compared to the average consumer. | N.A. | N.A. | N.A. | Brucks (1985) |
| Product involvement[a] | How important was the product for you at the time of purchase?<br>1. Very important<br>2. Of big concern to me<br>3. Very relevant<br>4. Meant a lot to me | 0.93/0.93 | 0.93/0.93 | 0.76/0.77 | Zaichkowsky (1985) |
| *WOM-type-specific resources* | | | | | |
| WOM-type-specific network size[a] | Within my social environment (friends, family, colleagues etc.), there are a lot of people who are familiar with the product/ service.<br>There are many ratings of the product/service online from other consumers.<br>Among my Facebook friends, many are familiar with the product/service.<br>Among my Twitter contacts, many are familiar with the product/service. | N.A. | N.A. | N.A. | New scale |
| WOM-type-specific tie strength[a] | The information I receive this way originates from people who are close to me. | N.A. | N.A. | N.A. | New scale |
| WOM-type-specific knowledge[d] | My abilities to find information about products and services in personal conversations are…<br>My abilities to find information about products and services on websites with reviews written by other consumers are…<br>My abilities to find information about products and services among my Facebook friends are…<br>My abilities to find information about products and services among my Twitter contacts are… | N.A. | N.A. | N.A. | Brucks (1985) |
| WOM-type-specific ease of access[a] | 1. I can access the information I am looking for at any time.<br>2. It is easy to get the information I am looking for.<br>3. It is generally not complicated to find the information I am looking for. | 0.92/0.90 | 0.92/0.90 | 0.79/0.77 | Tybout et al. (2005) |

Notes: [a]We obtained responses using seven-point scales, anchored by "Strongly disagree" (1) and "Strongly agree" (7). [b]We obtained responses using seven-point scales, anchored by "For a long time" (1), "For a while" (4), and "The product was new on the market" (7). [c]We obtained responses using seven-point scales, anchored by "I knew very little about the product" (1), "I know something about the product" (4), and "I knew a lot about the product" (7). [d]We obtained responses using seven-point scales, anchored by "Far below average" (1) and "Far above average" (7). Notes: AVE = average variance extracted. N.A. = not applicable.

the product"). We measured consumers' product involvement with four items from Zaichkowsky (1985).

Regarding the WOM type–specific resources, we asked consumers to rate their type-specific knowledge with one item for each of the WOM types (adapted from Brucks 1985) (1 = "far below average," 7 = "far above average"). For network size, we also used one item per WOM type (e.g.,: "In my personal surroundings there are many people who are very knowledgeable about the product" (f2f WOM)). As the measure of tie strength, respondents indicated the perceived closeness of their relationship with the people sending WOM information of each type. Finally, we measured ease of access with three items from Tybout et al. (2005).

### 4.3. Validity

We conducted a confirmatory factor analysis using SPSS AMOS 22 to assess the measurement properties of our product risk, utilitarian/hedonic character, evaluation difficulty, consumer extraversion, GOSIP, product involvement, and WOM type–specific ease of access scales. The results reveal a good overall fit of the model (root mean square error of approximation = 0.04, standardized root mean residual = 0.04; non-normed fit index = 0.97; comparative fit index = 0.98), as well as the solid psychometric properties of the measures. All standardized factor loadings exhibit statistical significance at $p < .001$, indicating convergent validity. The factor magnitudes range from 0.73 to 0.95 and demonstrate positive signs. Evidence of internal consistency stems from composite reliability (values ranging from 0.71 to 0.93), alpha scores (0.82 to 0.94), McDonald's omega (0.82 to 0.94) (Hayes & Coutts, 2020), and the average variance extracted (AVE; 0.55 to 0.79). We also achieve discriminant validity according to Fornell and Larcker's (1981) suggested criterion, because the AVE is greater than the squared correlation for each pair of factors. Table 3 contains the descriptive information and bivariate correlations.

Self-reported measures can be subject to respondent errors, which could create measurement errors in the research findings (MacKenzie & Podsakoff, 2012; Podsakoff et al., 2003). However, such concerns are not pressing for our research for several reasons. First, the self-reported behavioral measures we gather are unlikely to be influenced by social desirability. Most measures deal with the product or service, so social desirability is less of a concern; consumers only need to describe their factual shopping experiences. Two variables arguably might be subject to social desirability (consumer extraversion and GOSIP), but prior research has ruled out this link (Blazevic et al. 2014; Ones et al., 1996). Second, we asked respondents to recall a recent purchase of a product or service for which they received WOM beforehand. Following suggestions by MacKenzie and Podsakoff (2012), we eased their recall of this information by condensing the relevant time span to a maximum of three months and providing questions that facilitated their top-down retrieval. Specifically, we asked respondents to name the specific product and brand they bought, followed by several questions regarding the decision process (e.g., where they bought it, when).

Third, we designed the survey to avoid common method variance (CMV), such that we provided guarantees of anonymity, carefully crafted the scale items, and used different scale types. We adopted previously validated measures to increase validity whenever possible. For some measures (product newness; WOM type–specific network size, tie strength, and ease of access; the dependent variables), we constructed items and pretested them through a survey of 257 students. As Table 2 shows, all measures exhibited high reliability. Fourth, we tested for CMV effects post hoc. A marker variable technique, as recommended by Lindell and Whitney (2001), interprets the correlation between the marker variable and a theoretically unrelated variable as an estimate of CMV, such that the second-lowest positive correlation in the correlation matrix offers a conservative proxy for CMV (Chakravarty et al., 2014). We find no significant differences between the observed and adjusted correlation coefficients, so CMV is unlikely to be influential. Even if the average bias-detecting accuracy of this marker variable technique can be low (Richardson et al., 2009), the careful design of our questionnaire supports these results and suggests CMV has no relevant effects on the results.

### 4.4. Estimation

The dependent variable in each analyses is the respondent's usage of a specific WOM type, relative to his or her usage of the other WOM types. The resulting scores resemble percentage scores, ranging between 0 and 1 and undefined for other values, so ordinary least squares regression would not be an adequate estimation approach. We instead apply a multivariate fractional regression analysis (Murteira & Ramalho, 2016), developed specifically to handle fractional or proportional data (Papke & Wooldridge, 1996; Ramalho et al., 2011), to address the effects on multiple dependent variables simultaneously.[2]

In line with the specific nature of our data and research interest, we ran the fractional multinominal logit regression, based on a quasi-likelihood estimation, using the *fmlogit* command in Stata 13 (Buis, 2008). For all constructs measured with multiple items, we calculated the mean score and used it in all analyses. For the type resources, we calculated *relative* measures by dividing the WOM type–specific resource score by the sum of all type scores for the respective resource, similar to our treatment of the dependent variables.

### 4.5. Results

Among the 2,039 respondents, 73.4% used f2f WOM as part of their decision-making process, 48.4% used WOM on social media platforms, and 83.4% used IOS WOM as an information source, at least to a certain degree (i.e., score of 2 or higher on the 7-point scale). Table 4 contains the results of the fractional multinominal logit regression. To facilitate the interpretation, we report average marginal effects (AME), or the effect of a change in one regressor on the conditional mean of y (Cameron & Trivedi, 2010). For comparison purposes, we also report the results obtained by using three, distinct, one-part fractional logit regression models, for each WOM type (Appendix C), as well as those that emerged from an ordinary least squares regression with robust standard errors (Appendix D). We report the results of our hypotheses tests here, then discuss them in more detail in the following section.

*Effects of product characteristics*. For product risk, the results exhibit the pattern we predicted, with negative parameters for f2fWOM and SM WOM usage and a positive parameter for IOS WOM usage. However, only the negative parameter for SM WOM approaches significance, in line with $H_{1b}$. Regarding the utilitarian/hedonic product character, we find a negative effect of a product's utilitarian character on SM WOM usage, as proposed in $H_{2b}$. However, its utilitarian character had no effects on f2f WOM or IOS WOM. For product newness, the results offer support for $H_{3b}$, in the form of a positive effect on the use of SM WOM. However, we find a negative effect for newness on IOS WOM which approaches significance, opposite to $H_{3c}$ and no effect on f2f WOM. Finally, the results support the hypothesized positive effect of evaluation difficulty on SM WOM in $H_{4b}$ but reveal no significant effects of evaluation difficulty on f2f WOM or IOS WOM.

*Effects of consumer characteristics*. The results for consumer extraversion support $H_{5a}$, in that higher levels of consumer extraversion correspond with greater uses of f2f WOM. However, it has no effect on the two digital WOM types. The parallel concept of GOSIP exerts the expected positive effect on SM WOM, with regard to the share of search activities, as proposed in $H_{6b}$. In addition, we found a significant negative effect of GOSIP on IOS WOM, as proposed in $H_{6c}$ and no effect on f2f WOM. The effect of product knowledge on the use of SM WOM is positive, which contradicts our arguments for $H_{7b}$. Also, we find no effects on f2f or IOS WOM for this variable. A consumer's product involvement leads to lower search levels for f2f WOM and higher search levels for IOS WOM, in support of $H_{8a}$ and $H_{8c}$, whereas for SM WOM, the parameter is not significant.

*Effects of WOM type–specific resources*. For each WOM type, we consider the resources that match the respective type. Consumers' WOM type–specific knowledge positively influences their SM WOM choice when they search for information, in line with $H_{9a}$, but not their f2f WOM or IOS WOM choices. Moreover, we find positive effects of consumers' WOM type–specific network size for f2f WOM and SM WOM but not for IOS WOM choice; WOM type–specific tie strength positively affects f2f WOM and IOS WOM but not SM WOM choice. These findings offer partial support for both $H_{9b}$ and $H_{9c}$. For WOM type–specific ease of access, we identify the proposed positive effects for IOS WOM but not for SM WOM or f2f WOM, which implies partial support for $H_{9d}$.

[2] We are thankful to an anonymous reviewer for the suggestion.

**Table 3**
Correlation Matrix (n = 2,036).

| | M | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 4.48 | 1.80 | 1 | | | | | | | | | | | | | | | | | | | | | |
| 2 | 5.03 | 1.56 | .28[a] | 1 | | | | | | | | | | | | | | | | | | | | |
| 3 | 3.17 | 2.15 | -0.03 | -.05[b] | 1 | | | | | | | | | | | | | | | | | | | |
| 4 | 2.69 | 1.52 | .32[a] | .07[a] | .12[a] | 1 | | | | | | | | | | | | | | | | | | |
| 5 | 5.04 | 1.38 | .09[a] | .17[a] | -0.00 | -0.02 | 1 | | | | | | | | | | | | | | | | | |
| 6 | 3.76 | 1.70 | -0.00 | .12[a] | .19[a] | .13[a] | .32[a] | 1 | | | | | | | | | | | | | | | | |
| 7 | 4.59 | 1.61 | -.05[b] | .09[a] | .09[a] | -.06[a] | .18[a] | .14[a] | 1 | | | | | | | | | | | | | | | |
| 8 | 4.80 | 1.54 | .27[a] | .48[a] | 0.01 | .10[a] | .25[a] | .20[a] | .21[a] | 1 | | | | | | | | | | | | | | |
| 9 | 0.28 | 0.09 | -0.04 | 0.01 | -.12[a] | -.10[a] | .13[a] | -.18[a] | .09[a] | -0.04 | 1 | | | | | | | | | | | | | |
| 10 | 0.27 | 0.11 | -.16[a] | -.10[a] | .21[a] | 0.03 | -0.01 | .30[a] | .12[a] | -0.03 | -.35[a] | 1 | | | | | | | | | | | | |
| 11 | 0.34 | 0.13 | .20[a] | .09[a] | -.16[a] | 0.01 | -.07[a] | -.22[a] | -.17[a] | .07[a] | -.32[a] | -.72[a] | 1 | | | | | | | | | | | |
| 12 | 0.37 | 0.14 | .12[a] | .06[a] | -.22[a] | -.12[a] | .06[a] | -.33[a] | -0.02 | 0.03 | .39[a] | -.43[a] | .22[a] | 1 | | | | | | | | | | |
| 13 | 0.27 | 0.11 | -.08[a] | -.11[a] | .17[a] | .09[a] | -0.04 | .29[a] | 0.00 | -0.03 | -.30[a] | .57[a] | -.35[a] | -.54[a] | 1 | | | | | | | | | |
| 14 | 0.25 | 0.12 | -.05[b] | .05[b] | 0.03 | 0.01 | 0.01 | 0.03 | 0.01 | 0.01 | -.09[a] | -.10[a] | .16[a] | -.53[a] | -.36[a] | 1 | | | | | | | | |
| 15 | 0.29 | 0.07 | .08[a] | .05[b] | -.17[a] | -.10[a] | .15[a] | -.26[a] | -0.02 | 0.01 | .37[a] | -.37[a] | .16[a] | .47[a] | -.43[a] | -0.04 | 1 | | | | | | | |
| 16 | 0.28 | 0.09 | -.14[a] | -.11[a] | .17[a] | .06[a] | -0.00 | .30[a] | .06[b] | -0.04 | -.21[a] | .60[a] | -.45[a] | -.41[a] | .57[a] | -.12[a] | -.67[a] | 1 | | | | | | |
| 17 | 0.31 | 0.08 | .13[a] | .11[a] | -.13[a] | -0.03 | -.09[a] | -.24[a] | -.06[a] | .06[a] | 0.03 | -.51[a] | .55[a] | .25[a] | -.41[a] | .19[a] | .14[a] | -.72[a] | 1 | | | | | |
| 18 | 0.30 | 0.08 | .07[a] | .07[a] | -.16[a] | -.10[a] | .08[a] | -.26[a] | 0.01 | 0.04 | .35[a] | -.33[a] | .14[a] | .47[a] | -.40[a] | -.07[a] | .44[a] | -.35[a] | .20[a] | 1 | | | | |
| 19 | 0.27 | 0.10 | -.15[a] | -.10[a] | .19[a] | .08[a] | 0.01 | .30[a] | .05[b] | -0.03 | -.19[a] | .60[a] | -.49[a] | -.44[a] | .57[a] | -.09[a] | -.39[a] | .58[a] | -.49[a] | -.65[a] | 1 | | | |
| 20 | 0.32 | 0.09 | .15[a] | .08[a] | -.17[a] | -.09[a] | -.05[b] | -.25[a] | -.08[a] | 0.02 | 0.01 | -.53[a] | .59[a] | .29[a] | -.40[a] | .14[a] | .22[a] | -.47[a] | .56[a] | .11[a] | -.75[a] | 1 | | |
| 21 | 0.33 | 0.28 | -0.02 | -0.01 | -.12[a] | -.13[a] | .11[a] | -.16[a] | 0.04 | -.05[b] | .47[a] | -.08[a] | -.22[a] | .45[a] | -.23[a] | -.25[a] | .30[a] | -.13[a] | -0.04 | .31[a] | -.11[a] | -.06[b] | 1 | |
| 22 | 0.19 | 0.19 | -.14[a] | .13[a] | .25[a] | .11[a] | -0.01 | .32[a] | .11[a] | -.05[b] | -.17[a] | .54[a] | -.44[a] | -.44[a] | .49[a] | -0.02 | -.30[a] | .48[a] | -.41[a] | -.29[a] | .50[a] | -.45[a] | -.29[a] | 1 |
| 23 | 0.43 | 0.30 | .13[a] | -.09[a] | -.12[a] | -0.01 | -.09[a] | -.14[a] | -.12[a] | .08[a] | -.29[a] | -.36[a] | .57[a] | -0.03 | -.18[a] | .24[a] | -0.01 | -.27[a] | .38[a] | -0.03 | -.30[a] | .43[a] | -.67[a] | -.49[a] |

Notes: 1 = Risk of product; 2 = Utilitarian/hedonic character; 3 = Product newness; 4 = Evaluation difficulty; 5 = Consumer extraversion; 6 = GOSIP; 7 = Product knowledge; 8 = Product involvement; 9 = Network size f2f; 10 = Network size SM; 11 = Network size IOS; 12 = Tie strength f2f; 13 = Tie strength SM; 14 = Tie strength IOS; 15 = Knowledge f2f; 16 = Knowledge SM; 17 = Knowledge IOS; 18 = Ease of access f2f; 19 = Ease of access SM; 20 = Ease of access IOS; 21 = Extent of f2f usage; 22 = Extent of SM usage; 23 = Extent of IOS usage. f2f = face-to-face word of mouth. SM = social media platforms word of mouth. IOS = internet opinion site word of mouth. N.A. = not applicable. [a]$p < .01$ (two-tailed). [b]$p < .05$ (two-tailed).

**Table 4**
Results of multivariate fractional regression analyses.

| | f2f WOM | | | SM WOM | | | IOS WOM | | |
|---|---|---|---|---|---|---|---|---|---|
| | AME (SE) | z | p > \|z\| | AME (SE) | z | p > \|z\| | AME (SE) | z | p > \|z\| |
| **Product characteristics** | | | | | | | | | |
| Product risk | -0.001 (0.003) | −0.19 | 0.845 | -0.004† (0.002) | −1.78 | 0.075 | 0.005 (0.003) | 1.33 | 0.184 |
| Utilitarian/hedonic product | 0.005 (0.004) | 1.21 | 0.228 | -0.009** (0.003) | −3.22 | 0.001 | 0.004 (0.004) | 0.95 | 0.341 |
| Product newness | -0.002 (0.002) | −0.95 | 0.343 | 0.007** (0.002) | 4.23 | 0.000 | -0.005† (0.003) | −1.77 | 0.076 |
| Evaluation difficulty | -0.004 (0.003) | −1.18 | 0.239 | 0.007** (0.002) | 3.24 | 0.001 | -0.003 (0.004) | −0.94 | 0.350 |
| **Consumer characteristics** | | | | | | | | | |
| Consumer extraversion | 0.009† (0.005) | 1.86 | 0.063 | -0.005 (0.003) | −1.51 | 0.130 | -0.004 (0.005) | −0.84 | 0.404 |
| GOSIP | -0.002 (0.004) | −0.61 | 0.542 | 0.014** (0.003) | 5.07 | 0.000 | -0.012** (0.004) | −3.03 | 0.002 |
| Product knowledge | -0.002 (0.004) | −0.64 | 0.524 | 0.007** (0.003) | 2.88 | 0.004 | -0.005 (0.004) | −1.30 | 0.193 |
| Product involvement | -0.011* (0.004) | −2.54 | 0.011 | -0.001 (0.003) | −0.19 | 0.845 | 0.011* (0.004) | 2.51 | 0.012 |
| **WOM-type-specific resources** | | | | | | | | | |
| f2f WOM-type-specific knowledge | 0.154 (0.186) | 0.82 | 0.410 | 0.468** (0.148) | 3.17 | 0.002 | -0.623** (0.189) | −3.29 | 0.001 |
| f2f WOM-type-specific network size | 0.811** (0.186) | 4.36 | 0.000 | 0.074 (0.135) | 0.55 | 0.581 | -0.886** (0.191) | −4.64 | 0.000 |
| f2f WOM-type-specific tie strength | 0.400* (0.181) | 2.19 | 0.028 | -0.352** (0.119) | −2.96 | 0.003 | -0.044 (0.186) | −0.24 | 0.812 |
| f2f WOM-type-specific ease of access | 0.253 (0.188) | 1.35 | 0.177 | 0.027 (0.132) | 0.20 | 0.839 | -0.280 (0.199) | −1.40 | 0.160 |
| SM WOM-type-specific knowledge | -0.060 (0.202) | −0.30 | 0.765 | 0.598** (0.154) | 3.89 | 0.000 | -0.537* (0.210) | −2.56 | 0.010 |
| SM WOM -type-specific network size | 0.296 (0.210) | 1.41 | 0.159 | 0.386** (0.152) | 2.54 | 0.011 | -0.682** (0.216) | −3.16 | 0.002 |
| SM WOM -type-specific tie strength | -0.362† (0.194) | −1.87 | 0.062 | 0.142 (0.136) | 1.04 | 0.296 | 0.220 (0.200) | 1.10 | 0.269 |
| SM WOM -type-specific ease of access | 0.044 (0.224) | 0.20 | 0.843 | 0.171 (0.156) | 1.10 | 0.272 | -0.216 (0.229) | −0.94 | 0.347 |
| IOS WOM-type-specific knowledge | -0.107 (0.175) | −0.61 | 0.540 | 0.131 (0.138) | 0.95 | 0.343 | -0.024 (0.183) | −0,13 | 0.897 |
| IOS WOM -type-specific network size | -0.255 (0.185) | −1.38 | 0.168 | -0.046 (0.131) | −0.35 | 0.725 | 0.301 (0.189) | 1.59 | 0.112 |
| IOS WOM -type-specific tie strength | -0.314† (0.180) | −1.75 | 0.080 | -0.056 (0.121) | −0.46 | 0.644 | 0.370* (0.183) | 2.02 | 0.044 |
| IOS WOM -type-specific ease of access | -0.170 (0.193) | −0.88 | 0.378 | -0.296* (0.133) | −2.23 | 0.026 | 0.466* (0.197) | 2.37 | 0.018 |
| Constant | | | | | | | | | |
| Number of observations | 2,039 | | | 2,039 | | | 2,039 | | |

Notes: f2f WOM = face-to-face word of mouth. SM WOM = social media platforms word of mouth. IOS WOM = Internet opinion sites word of mouth. Coefficients are unstandardized coefficients from the multinominal fractional regression analysis; number in parentheses are robust standard errors, and AME are average marginal effects. ** $p < .01$. * $p < .05$ † = $p < .10$.

## 5. Discussion

### 5.1. Key insights from hypothesis testing

The pattern of results for the product characteristics (i.e., product risk, utilitarian/hedonic character, product newness, evaluation difficulty) is consistent, if not identical, with our theoretical arguments. Specifically, product characteristics determine the search activity that consumers dedicate to social media WOM (SM WOM), as we predicted. However, their contributions to determining how much search effort consumers allocate to face-to-face WOM (f2f WOM) and Internet opinion sites WOM (IOS WOM) are limited, and none of the proposed effects receive empirical support. For more traditional WOM types, the characteristics of the product appear to have limited importance when it comes to search effort allocations. These findings are reinforced by the R-square value that we find in a model that includes *only* the product characteristics: Product characteristics account for 11% of the explained variance of SM WOM, whereas for f2f WOM and IOS WOM, they can explain just 3%.

For consumer characteristics, the patterns of results are more differentiated. For example, considering the related concepts of consumer extraversion and GOSIP, we find corresponding patterns. Extraversion determines search activity through f2f WOM, and GOSIP explains how much consumers use SM WOM, as theoretically proposed. The lack of impact of extraversion on SM WOM may result from its "hybrid" nature—that is, an online source that, unlike IOS WOM, provides extensive space for articulation and social visibility. Furthermore, interaction is a focal element of GOSIP (Blazevic et al., 2014), and we posit that the interactive nature of personal f2f WOM communication might counteract the negative impact of the offline environment for consumers high in this propensity.

We do not find evidence of the proposed negative effect of product involvement on SM WOM usage. We suspect the many-to-many character of the SM WOM type is the key: It provides consumers with access to a potentially large network of consumer experiences, in conflict with the short nature of SM messages. The results for product knowledge also run counter to our theory-inspired expectations, with no significant effects for f2f WOM or IOS WOM and a positive (cf. negative) effect for SM WOM. Perhaps knowledgeable consumers value diverse information (which SM WOM provides, through the variety of network members) and the possibility of lively, continuous conversations more than they feel limited by the imposed brevity. Parsimonious SM WOM statements about a specific topic or problem even might be valued by consumers already in possession of high (general) knowledge.

For the other two WOM types, the advantages are equivalent to their respective limitations. That is, f2f WOM offers rich information but limited opportunities for self-expression and access to other experts, and IOS WOM offers rich information but limited opportunities for discussing complex, challenging expert questions. Overall, consumer characteristics offer the most explanatory power for SM WOM searches (12% of variance), but they also are meaningful for f2f WOM (6%) and IOS WOM (5%).

Most of the WOM type–specific resource hypotheses receive support, with the exception of the proposed effect of consumers' knowledge on their usage of IOS WOM. This result might reflect the limited variation among respondents; most consumers simply have become familiar with the process of searching for information on review websites. The same explanation may apply for the lack of effect of ease of access to f2f WOM, such that this access varies relatively little among modern consumers. The importance of WOM type–specific resources also is evident in the high degrees of variance explained, such that WOM type–specific resources explain as much as 39% of SM WOM usage, 36% of IOS WOM usage, and 31% of f2f WOM usage.

### 5.2. Ordering WOM types: Insights into consumers' search journeys

To augment our analysis of WOM usage, we investigate the process by which consumers use different WOM information sources, to establish some initial insights into the stages in the search journey in which consumers prefer to find and use specific WOM sources. With the same participant sample, we asked the respondents to put the different WOM sources that they used in order, using a drag-and-drop function, to reflect the order in which they consulted those sources when searching for information about the focal product. There were four options in the drag function: f2f conversations, online opinion platforms, Facebook, and Twitter. Each respondent manipulated only those sources that he or she indicated having used during the purchase process.

When we combine the different WOM types, we identify 55 total journey combinations. To ensure sufficient statistical power, we focus on the subsample of combinations in which consumers used at least three of the four WOM sources (i.e., conversations as f2f WOM, WOM on Internet opinion sites as IOS WOM, and WOM on Facebook or Twitter as SM WOM). This step produced six combinations and a sample of 1,075 respondents. Facebook is more popular in our sample (58% of respondents used Facebook, whereas only 40% used Twitter), so we prioritize these journeys; when we replicate the analyses with Twitter instead of Facebook (n = 804), the z-test shows no differences between samples (p-values ranging between 0.617 and 0.127).

Table 5 provides a detailed description of the different journeys: 55.7% of respondents searched f2f WOM first, 36.0% started their search journey with IOS WOM, and only 8.3% acquired SM WOM first. The two most frequent journeys were f2f–IOS–SM (32.6%) and IOS–f2f–SM (25.2%). In contrast, the least frequented paths included two online–offline switches, such that only 3.7% of respondents moved from SM WOM to f2f WOM and then to IOS WOM. Most consumers used SM WOM as the last source (58.0%), suggesting that this relatively newer WOM type might tip the scales at the end of consumers' decision processes.

Building on these insights, we investigate which factors cause consumers to choose a certain journey. In multinomial logistic regressions for each WOM type, we include the rank order in which a consumer used each WOM type as the dependent variable. As explanatory variables, we rely on the variables from our prior analysis (i.e., product characteristics, consumer characteristics, WOM type–specific resources). All three models are significant, with Nagelkerke pseudo R-square values of 0.087 for IOS WOM, 0.090 for f2f WOM, and 0.139 for SM WOM. Table 6 summarizes the results; Appendix E reports the full regression results.

The different sequences also indicate different drivers. For example, the probability that a consumer uses f2f WOM as the first rather than the last information source increases when the consumer knows relatively more people in her or his offline network who can provide relevant information. A similar effect appears for IOS and SM WOM. Thus, the characteristics of the consumers' networks exert strong influences.

In line with our findings about IOS WOM usage, a consumer's extraversion lowers the chances that it is the first or second source, compared with its chances of being used last. For both digital WOM types, a consumer's relative tie strength raises the chances that either of them will be used as a first or second information source. If the possible sender of information is perceived as closer—relative to the other WOM types—the consumer starts the search journey with the source that represents his or her closest relationships. For all three WOM types, the ease of access raises the chances that it will be chosen as a second source in the journey.

**Table 5**
Consumer Journeys.

| | | Frequency | Percentage | Total (per WOM type chosen first) |
|---|---|---|---|---|
| **Usage sequence** | f2f = 1, IOS = 2, SM = 3 | 350 | 32.6 | |
| | f2f = 1, SM = 2, IOS = 3 | 249 | 23.2 | 55.7 |
| | IOS = 1, f2f = 2, SM = 3 | 271 | 25.2 | |
| | IOS = 1, SM = 2, f2f = 3 | 116 | 10,8 | 36.0 |
| | SM = 1, IOS = 2, f2f = 3 | 49 | 4.6 | |
| | SM = 1, f2f = 2, IOS = 3 | 40 | 3.7 | 8.3 |
| | Total amount | 1075 | 100,0 | |

Notes: f2f = face-to-face word of mouth. SM = social media platforms word of mouth. IOS = internet opinion sites word of mouth.

### 5.3. Implications and conclusions

This study is the first to investigate, theoretically and empirically, how consumers use three distinct, popular WOM types when searching for purchase-related information. It represents a response to calls for a richer understanding of WOM, beyond a simple online–offline dichotomy (e.g., Berger & Iyengar, 2013; Hennig-Thurau et al., 2015), by providing insights into the differences among one offline and two digital types of WOM. Moreover, we identify several determinants of consumers' uses of different WOM types when searching for information, based on a conceptual framework derived from prior research.

The results, reflecting the stated purchase-related behavior of more than 2,000 consumers, demonstrate that various product characteristics, consumer characteristics, and WOM type–specific resources help explain reliance on different WOM sources. Overall, the findings suggest customers take a cost–benefit approach in their WOM search journeys, as reflected in the average marginal effects and degree of explained variance, which are higher for WOM type–specific resources. Consumers turn to the WOM type that provides them with the largest network of potential product experts and where they perceive that the senders of the information are close to them. For IOS WOM, the WOM type–specific ease of accessibility is also important. Therefore, the results confirm that consumers choose their WOM types carefully, rather than arbitrarily. The three types WOM are not just random substitutes for one another.

This study also offers initial insights into the order in which people turn to different WOM types during their consumer journeys. Most respondents (53%) in our representative sample reported that they used all three WOM types when searching for information, which suggests that the different types coexist and offer unique benefits to consumers, instead of serving as substitutes. The majority started with f2f WOM or IOS WOM as their first source; only a few started on social media (SM WOM). These findings shed new light on the determinants of consumers' journeys; multinomial logit regression analyses reveal that consumers do not plan their journeys arbitrarily.

### 5.4. Managerial implications

Managing WOM is difficult, but marketers can learn from it, as well as potentially influence consumers' articulations and usages of it. In particular, they should pursue different strategies to monitor and manage different WOM types. Strategies that enhance the effectiveness of one type of WOM do not necessarily have similar effects on other WOM types. Depending on their target consumers and products, marketers should acknowledge and leverage the differences among WOM types, with their distinct effects on consumers' decisions. There is no such thing as "WOM in general," and generalizing insights drawn from one WOM type to all WOM is wrong.

Different product and consumer characteristics influence the usage of WOM types, which can provide a sort of road map for managers. For example, if a firm's target market consists of consumers who enjoy online interactions, managers should try to stimulate consumer reviews on social media (i.e., on average, a one-unit increase in online interaction is associated with a 1.4% increase in SM WOM usage). Managers of complex products should provide detailed information about products on Facebook and other social media too, because consumers prefer such social networks when confronted with a difficult decision (i.e., on average, a one-unit increase in evaluation difficulty is linked to a 0.7% increase in SM WOM usage). Triggering the WOM articulation motivations of consumers who already have purchased then might help others who are searching for answers (Hennig-Thurau et al., 2004). Firms can build Q&A forums or communities in social media to encourage exchanges of information between product enthusiasts and information

**Table 6**
Drivers Of Different Consumer Journeys.

| Used as ... | f2f WOM | SM WOM | IOS WOM |
|---|---|---|---|
| **1st source** | (+) WOM type–specific network size f2f WOM**<br>(+) WOM type–specific tie strength f2f WOM*<br>(+) WOM type–specific ease of access f2f WOM* | (-) Product risk*<br>(+) WOM type–specific network size SM WOM**<br>(+) WOM type–specific tie strength SM WOM* | (+) Product newness*<br>(-) Consumer extraversion**<br>(+) GOSIP**<br>(+) WOM type–specific network size IOS WOM**<br>(+) WOM type–specific tie strength IOS WOM** |
| **2nd source** | (+) WOM type–specific ease of access f2f WOM** | (+) Utilitarian/hedonic product*<br>(+) Consumer extraversion*<br>(+) WOM type–specific network size SM WOM**<br>(+) WOM type–specific tie strength SM WOM**<br>(+) WOM type–specific ease of access SM WOM* | (-) Consumer extraversion**<br>(+) WOM type–specific tie strength IOS WOM**<br>(+)WOM type–specific ease of access IOS WOM** |
| **3rd source** | | Comparative category | |

Notes: f2f WOM = face-to-face word of mouth. SM WOM = social media platforms word of mouth. IOS WOM = internet opinion sites word of mouth. ** $p < .01$. * $p < .05$.

seekers and thus help consumers faced with difficult options.

When it comes to monitoring WOM, the effectiveness of stimulating conversations about products and brands needs to be measured according to the WOM type in question (see Lovett et al., 2013). Measures of conversations in social networks might be appropriate for hedonic products, but for highly involved consumers (and highly involving products), communication through IOS matters most (a one-unit increase in involvement is associated with 1.1% more IOS WOM usage). Not all successful initiatives translate into specific results, such as likes and comments on Facebook, so managerial incentives should be designed with this constraint in mind.

Managing customers' journeys is a particularly hot topic in marketing (e.g., Kuehnl et al., 2019; Voorhees et al., 2017), and our findings offer further insights that might be of managerial value. Managers could specify different WOM types in their journey-management effort, just as they do other information sources or touchpoints. Researchers recognize the gaps of knowledge surrounding the use of WOM in different stages of the consumer journey (Jang et al., 2012), even though WOM accounts for approximately two-thirds of consumer touchpoints (Court et al., 2009). Because face-to-face conversations are the starting point of most journeys in our sample, seeding campaigns that offer products on a trial basis might prove effective, to the extent that they spark offline conversations. But even following that effort, companies should create detailed plans to attract consumers' attention and increase their purchase intentions. That is, they should plan to trigger offline conversations first, consolidate consumers' attention by offering information on IOSs, and finally encourage a purchase through social media information, offered mostly at the end of the journey. This effort is critical, even if it raises some measurement difficulties (Libai et al., 2013), in that "cutting-edge journeys succeed because they create new value for customers: Customers stay because they benefit from the journey itself" (Edelman & Singer, 2015, p. 3).

### 5.5. Research implications

This research deepens our understanding of consumers' allocations of search effort across WOM types and the sequence of WOM types within the consumer journey. It accordingly lays a foundation for further research in several areas.

*Measuring offline WOM*. Our study underlines the need to distinguish among WOM types. It also rejects an implicit assumption, namely, that findings from online data can be transferred to offline WOM. Scholars and managers must take care when generalizing their findings (Lovett et al., 2013)—a caution that reopens questions about how to analyze offline WOM. Because information gets exchanged in private conversations, direct observation is difficult (Godes & Mayzlin, 2004). The use of a verbal protocol analysis might be a promising way to gather further insights and understand in more detail what kind of content-related overlap exists between digital WOM and offline WOM.

*Relationships among WOM types*. Our results specify distinct characteristics of the three WOM types, suggesting the need to analyze their interrelationships. Do all consumers, or some of them, actively use the different WOM types as complements or as substitutes? Our finding that consumers start their journey with either f2f WOM or IOS WOM might seem intuitive, especially for f2f WOM, because conversations about products are part of people's everyday lives (Berger & Iyengar, 2013). However, for IOS WOM, the reasoning is less straightforward. Consumers actively search for reviews on IOS rather than coming across a review by accident. What makes consumers turn to IOS WOM before asking friends or followers in SM WOM? Does SM WOM actually represent a tipping point before consumers click on the "buy" button?

*Adding more WOM types to the landscape*. Our study differentiates online- and offline-based WOM types, as well as the two digital formats. We focus on Facebook and Twitter, but there might be room for further research on relatively newer WOM platforms. Whereas we find no differences between the determinants of two social media platforms, the results might differ for other, unique platforms. How do content-based platforms like TikTok, Instagram, and Pinterest fit into the WOM landscape? Can recommendations in the form of shared or pinned pictures and videos be classified as WOM, or are they a new, distinct phenomenon? What effect do such platforms have on consumer information search and consumption behavior?

*Digital consumer journeys*. The rise of new technologies creates a plethora of information sources for consumers looking for product information. These technologies also offer new possibilities for marketing managers and scholars to track consumer behavior and gain deeper insights, particularly regarding *how* the different WOM types inform the consumer journey (Jang et al., 2012). Our R-square measures are relatively small, suggesting that consumer characteristics, product characteristics, and WOM type–specific resources are not the only determinants of consumer journeys. Including classic elements from consumer experience research, such as previous experience with the product (or brand), price, or service interface (Verhoef et al., 2009), might produce a more detailed view. In summary, we contribute to WOM literature by establishing that searches for online and offline WOM types differ significantly, particularly at different stages in the digital consumer journey.

### 5.6. Limitations

As with all empirical research, a number of limitations exist that require consideration. First, we capture reports of real behavior, instead of using an artificial experimental stimulus. Thus, participants' answers are necessarily context specific, reflecting each person's unique situation. The large sample of 2,039 respondents helps mitigate this concern, because this bias likely arises only for rare exceptions, which are part of the population we want to investigate. Second, our research design might induce recall biases. To minimize this risk, we excluded people who did not remember their recent purchase decisions, however participants in our setting always provide answers with regards to their subjective memories (Kuusela and Paul, 2000). Third, while endogeneity is a consequence of many research designs, it can bias results in cross-sectional observational data (Sande & Ghosh, 2018). Additional research should consider more potential confounds (e.g., trust, Internet savvy), which were not in the focus of our investigation. Fourth, while we designed the questionnaire thoroughly (e.g., measuring independent and dependent variable with different types of scales) and provide a formal test of potential common method bias, we cannot fully rule out its existence (Baumgartner et al., 2021). Fifth, another limitation of our sample is the cultural context in which the data collection took place. Future research should investigate if there are cultures differences in consumers' usage of different WOM types for product information search in other countries. Sixth, our focus on WOM allows us to draw a rich, differentiated picture of search processes, but it also leaves room for studies that address other antecedents (e.g., time it takes for different people to use different WOM types, availability in certain situations, etc.). In this effort, it would be interesting to learn about the composition of and interplay among other information sources, such as retailer websites or expert reviews for example.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix A. Quota sampling by the market research company

| | Representative Statistics | Target Values for N = 2,500 | Actual Quota | Actual Sample (N = 2,502) |
|---|---|---|---|---|
| **Gender** | | | | |
| Male | 50.0% | 1,250 | 49.7% | 1,243 |
| Female | 50.0% | 1,250 | 50.3% | 1,259 |
| **Age** | | | | |
| 16–24 | 27.0% | 675 | 26.7% | 669 |
| 15–34 | 21.0% | 525 | 21.6% | 540 |
| 35–44 | 28.0% | 700 | 27,9% | 697 |
| 45–54 | 15.0% | 375 | 15.2% | 380 |
| 55–64 | 9,0% | 225 | 8.6% | 216 |
| **Education** | | | | |
| No or primary school | 33% | 825 | 22.2% | 555 |
| Middle school | 30% | 750 | 36,0% | 901 |
| High school education or University degree | 37% | 925 | 41,8% | 1,046 |

Notes: The acquisition of participants based on representative quota sampling for German social media users was conducted by the international market research company Kantar Lightspeed GMI.

## Appendix B. Social network–specific regression results

| | SM WOM/Facebook | | SM WOM/Twitter | |
|---|---|---|---|---|
| | Coefficients (SE) | AME | Coefficients (SE) | AME |
| **Product characteristics** | | | | |
| Product risk | -0.031 (0.016) | -0.004 | -0.080** (0.022) | -0.007** |
| Utilitarian/hedonic product | 0.070** (0.019) | 0.009** | 0.049 (0.028) | 0.004 |
| Product newness | 0.058** (0.012) | 0.008** | 0.063** (0.015) | 0.006** |
| Evaluation difficulty | 0.057** (0.016) | 0.008** | 0.110** (0.021) | 0.010** |
| **Consumer characteristics** | | | | |
| Consumer extraversion | 0.000 (0.022) | 0.000 | -0.053 (0.028) | -0.005 |
| GOSIP | 0.106** (0.020) | 0.014** | 0.139** (0.027) | 0.012** |
| Product knowledge | 0.054** (0.018) | 0.007** | 0.045 (0.024) | 0.004 |
| Product involvement | -0.011 (0.020) | -0.001 | -0.020 (0.027) | -0.002 |
| **WOM-type-specific resources** | | | | |
| WOM type–specific knowledge | 2.138** (0.491) | 0.282** | 2.907** (0.567) | 0.261** |
| WOM type–specific network size | 3.672** (0.437) | 0.485** | 3.904** (0.529) | 0.350** |
| WOM type–specific tie strength | 2.253** (0.369) | 0.297** | 1.752** (0.476) | 0.157** |
| WOM type–specific ease of access | 2.802** (0.492) | 0.370** | 2.931** (0.616) | 0.263** |
| Constant | −5.178** (0.225) | | −5.362** (0.222) | |
| $R^2$-type measure | 0.406 | | 0.526 | |
| Akaike information criterion | 0.626 | | 0.454 | |
| Number of observations | 2,039 | | 2,039 | |

Notes: SM WOM/Facebook = social media platforms word of mouth via Facebook. SM WOM/Twitter = social media platforms word of mouth via Twitter. Coefficients are unstandardized coefficients from the fractional regression analysis; number in parentheses are robust standard errors, and AME are average marginal effects. Z-tests between models showed no significant differences for any of the model variables (p-values ranging between 0.834 and 0.163). ** $p < .01$. * $p < .05$.

## Appendix C:. Results of separate fractional regression analyses

| | f2f WOM | | SM WOM | | IOS WOM | |
|---|---|---|---|---|---|---|
| | Coefficients (SE) | AME | Coefficients (SE) | AME | Coefficients (SE) | AME |
| **Product characteristics** | | | | | | |
| Product risk | -0.023 (0.017) | -0.005 | -0.036* (0.016) | -0.005* | 0.020 (0.017) | 0.004 |
| Utilitarian/hedonic product | 0.009 (0.020) | 0.002 | -0.057** (0.019) | -0.008** | 0.010 (0.021) | 0.002 |
| Product newness | -0.005 (0.013) | -0.001 | 0.052** (0.012) | 0.007** | -0.014 (0.013) | -0.003 |
| Evaluation difficulty | -0.031 (0.018) | -0.006 | 0.052** (0.016) | 0.007** | -0.013 (0.017) | -0.003 |
| **Consumer characteristics** | | | | | | |
| Consumer extraversion | 0.060* (0.024) | 0.012* | 0.001 (0.022) | 0.000 | -0.079** (0.022) | -0.017** |
| GOSIP | 0.018 (0.019) | 0.004 | 0.096** (0.019) | 0.013** | 0.016 (0.018) | 0.003 |
| Product knowledge | 0.012 (0.019) | 0.002 | 0.060** (0.017) | 0.008** | -0.031 (0.019) | -0.007 |
| Product involvement | -0.056** (0.021) | -0.011** | -0.020 (0.020) | -0.003 | 0.055* (0.023) | 0.012* |
| **WOM-type-specific resources** | | | | | | |
| WOM type–specific knowledge | 0.288 (0.525) | 0.057 | 2.278** (0.487) | 0.308** | 0.445 (0.462) | 0.094 |
| WOM type–specific network size | 4.658** (0.397) | 0.920** | 3.320** (0.433) | 0.449** | 4.797** (0.342) | 1.012** |
| WOM type–specific tie strength | 2.727** (0.263) | 0.539** | 2.258** (0.372) | 0.305** | 1.916** (0.265) | 0.404** |
| WOM type–specific ease of access | 0.736 (0.460) | 0.145 | 2.802** (0.494) | 0.379** | 1.961** (0.446) | 0.414** |
| Constant | −3.390** (0.213) | | −5.090** (0.220) | | −3.014** (0.208) | |
| $R^2$-type measure | 0.322 | | 0.424 | | 0.368 | |
| Akaike information criterion | 0.891 | | 0.637 | | 0.938 | |
| Number of observations | 2,039 | | 2,039 | | 2,039 | |

Notes: f2f WOM = face-to-face word of mouth. SM WOM = social media platforms word of mouth. IOS WOM = Internet opinion sites word of mouth. We ran a one-part fractional logit regression model, based on a quasi-likelihood estimation, using the ‘frm’ command in Stata 13 (Ramalho, 2012). Coefficients are unstandardized coefficients from the fractional regression analysis; number in parentheses are robust standard errors, and AME are average marginal effects. ** $p < .01$. * $p < .05$. AME over 1 can be explained by a regression slope which is changing quickly, leading to an approximation above the natural threshold of 1. In this case the AME can be interpreted as 1.

## Appendix D:. Results of ordinary least squares regression analyses

| | f2f WOM | | SM WOM | | IOS WOM | |
|---|---|---|---|---|---|---|
| | Coefficients | Robust S.E. | Coefficients | Robust S.E. | Coefficients | Robust S.E. |
| **Product characteristics** | | | | | | |
| Product risk | -0.004 | 0.003 | -0.005* | 0.002 | 0.004 | 0.004 |
| Utilitarian/hedonic product | 0.003 | 0.004 | -0.007* | 0.003 | 0.002 | 0.004 |
| Product newness | -0.001 | 0.003 | 0.008** | 0.002 | -0.004 | 0.003 |
| Evaluation difficulty | -0.007 | 0.003 | 0.009** | 0.002 | -0.003 | 0.004 |
| **Consumer characteristics** | | | | | | |
| Consumer extraversion | 0.011* | 0.005 | -0.003 | 0.003 | -0.017** | 0.005 |
| GOSIP | 0.002 | 0.004 | 0.012** | 0.002 | 0.003 | 0.004 |
| Product knowledge | 0.002 | 0.004 | 0.007** | 0.002 | -0.006 | 0.004 |
| Product involvement | -0.011* | 0.004 | -0.003 | 0.003 | 0.011 | 0.005 |
| **WOM-type-specific resources** | | | | | | |
| WOM type–specific knowledge | 0.080 | 0.103 | 0.202** | 0.052 | 0.100 | 0.095 |
| WOM type–specific network size | 0.960** | 0.076 | 0.424** | 0.051 | 1.042** | 0.066 |
| WOM type–specific tie strength | 0.558** | 0.054 | 0.265** | 0.044 | 0.377** | 0.052 |
| WOM type–specific ease of access | 0.170 | 0.091 | 0.266** | 0.048 | 0.433** | 0.091 |
| Constant | -0.210** | 0.040 | -0.168** | 0.021 | -0.151** | 0.041 |
| $R^2$ | 0.318 | | 0.410 | | 0.364 | |
| RMSE | 0.228 | | 0.145 | | 0.243 | |
| Number of observations | 2,039 | | 2,039 | | 2,039 | |

Notes: f2f WOM = face-to-face word of mouth. SM WOM = social media platforms word of mouth. IOS WOM = internet opinion sites word of mouth. Coefficients are unstandardized coefficients from ordinary least squares regression analysis with robust standard errors. Robust S.E. are robust standard errors. ** $p < .01$. * $p < .05$.

## Appendix E. Multinomial logistic regressions for WOM types ranks

| | | f2f WOM | | | SM WOM | | | IOS WOM | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Coefficients | Exp (B) | Wald | Coefficients | Exp (B) | Wald | Coefficients | Exp (B) | Wald |
| Used as first source | Constant | −2.522** | | 9.541 | −7.040** | | 28.032 | −3.430** | | 21.526 |
| | **Product characteristics** | | | | | | | | | |
| | Product risk | 0.083 | 1.086 | 1.945 | -0.150* | 0.861 | 3.931 | 0.002 | 1.002 | 0.002 |
| | Utilitarian/hedonic product | -0.025 | 1.026 | 0.123 | 0.027 | 0.973 | 0.087 | -0.052 | 1.053 | 0.668 |
| | Product newness | -0.057 | 0.944 | 1.571 | -0.053 | 0.948 | 0.804 | 0.085* | 1.089 | 4.456 |
| | Evaluation difficulty | 0.000 | 1.000 | 0.000 | 0.008 | 1.008 | 0.009 | -0.050 | 0.951 | 0.805 |

(continued on next page)

(*continued*)

| | | f2f WOM | | | SM WOM | | | IOS WOM | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Coefficients | Exp (B) | Wald | Coefficients | Exp (B) | Wald | Coefficients | Exp (B) | Wald |
| | **Consumer characteristics** | | | | | | | | | |
| | Consumer extraversion | 0.047 | 1.049 | 0.297 | 0.180 | 1.197 | 2.665 | -0.269** | 0.764 | 13.434 |
| | GOSIP | -0.077 | 0.926 | 0.892 | -0.084 | 0.920 | 0.768 | 0.169** | 1.184 | 6.768 |
| | Product knowledge | -0.017 | 0.983 | 0.061 | 0.117 | 1.124 | 1.642 | -0.046 | 0.955 | 0.574 |
| | Product involvement | -0.036 | 0.965 | 0.205 | -0.080 | 0.923 | 0.647 | 0.127 | 1.135 | 3.301 |
| | **WOM type–specific resources** | | | | | | | | | |
| | WOM type–specific knowledge | 2.122 | 8.346 | 1.167 | 0.861 | 2.366 | 0.150 | -0.455 | 0.634 | 0.067 |
| | WOM type–specific network size | 5.066** | 158.571 | 7.188 | 6.574** | 716.361 | 9.785 | 5.430** | 228.220 | 14.044 |
| | WOM type–specific tie strength | 2.477* | 11.908 | 3.937 | 4.556* | 95.161 | 5.153 | 4.881** | 131.733 | 18.822 |
| | WOM type–specific ease of access | 4.395* | 81.018 | 4.896 | 4.527 | 92.473 | 3.077 | 3.140 | 23.112 | 3.069 |
| Used as second source | Constant | −2.787** | | 9.844 | −4.035** | | 34.214 | −2.458** | | 11.411 |
| | **Product characteristics** | | | | | | | | | |
| | Product risk | 0.081 | 1.085 | 1.617 | 0.000 | 1.000 | 0.000 | 0.028 | 1.028 | 0.276 |
| | Utilitarian/hedonic product | -0.104 | 1.109 | 1.701 | 0.134* | 0.875 | 5.909 | -0.077 | 1.080 | 1.545 |
| | Product newness | -0.061 | 0.941 | 1.477 | -0.059 | 0.943 | 2.801 | 0.055 | 1.056 | 1.904 |
| | Evaluation difficulty | -0.060 | 0.942 | 0.748 | 0.076 | 1.079 | 2.519 | -0.085 | 0.918 | 2.364 |
| | **Consumer characteristics** | | | | | | | | | |
| | Consumer extraversion | 0.040 | 1.041 | 0.178 | 0.135* | 1.144 | 4.325 | -0.188* | 0.828 | 6.920 |
| | GOSIP | -0.121 | 0.886 | 1.882 | -0.085 | 0.918 | 2.125 | 0.067 | 1.069 | 1.163 |
| | Product knowledge | -0.015 | 0.985 | 0.040 | 0.026 | 1.026 | 0.237 | -0.030 | 0.971 | 0.251 |
| | Product involvement | 0.027 | 1.027 | 0.097 | -0.054 | 0.948 | 0.789 | 0.084 | 1.088 | 1.535 |
| | **WOM type–specific resources** | | | | | | | | | |
| | WOM type–specific knowledge | 2.786 | 16.218 | 1.730 | 0.863 | 2.371 | 0.417 | -0.916 | 0.400 | 0.283 |
| | WOM type–specific network size | 1.877 | 6.532 | 0.861 | 4.745** | 114.998 | 14.380 | 2.605 | 13.538 | 3.364 |
| | WOM type–specific tie strength | 0.564 | 1.758 | 0.169 | 3.494** | 32.907 | 9.150 | 2.972** | 19.527 | 7.327 |
| | WOM type–specific ease of access | 6.466** | 642.928 | 9.024 | 3.486* | 32.648 | 5.893 | 5.263** | 193.046 | 9.088 |
| | Cox and Snell $R^2$ | 0.077 | | | 0.115 | | | 0.077 | | |
| | Nagelkerke $R^2$ | 0.090 | | | 0.139 | | | 0.087 | | |
| | McFadden | 0.041 | | | 0.069 | | | 0.037 | | |
| | Number of observations | 1075 | | | 1075 | | | 1075 | | |

Notes: f2f WOM = face-to-face word of mouth. SM WOM = social media platforms word of mouth. IOS WOM = Internet opinion sites word of mouth. Reference category: used as third source. Coefficients are unstandardized coefficients from multinomial logistic regression analysis. Exp (B) are odds ratios. ** $p < .01$. * $p < .05$.

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