Understanding Electronic Word of Behavior: Conceptualization of the Observable Digital Traces of Consumers' Behaviors

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Abstract

The widespread digitization of consumers' daily lives entails a plethora of digital traces of consumers' behaviors. These traces can be turned into meaningful communicative and observable content by the services that possess the trace data. While extant research has empirically showed this to have a significant impact on consumer choices we argue that the phenomenon is undertheorized. In this theoretical paper, we conceptualize this kind of observable behavior-based information as '*Electronic Word of Behavior' (eWOB)* and define it as "*published accounts of behavior, based on the unobservable digital traces of consumers' behaviors".* We characterize eWOB as an instantiation of Digital Trace Data and situate it within the established concepts of Social Interactions and Electronic Word of Mouth (eWOM). By drawing on extant empirical research and constructs from Digital Trace Data, Social Interactions and eWOM, we propose a framework for eWOB that highlights its unique characteristics and design dimensions.

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Introduction

Almost everything we as human beings and as consumers do online leaves a digital trace of our online behavior. When we listen to music on Spotify, Spotify logs the time, location, duration, and artist of that listening activity along with a plethora of other data about our listening behavior. Some of these 'digital trace data' are used by recommendation engines and help the service give us more relevant suggestions for what to listen to, read, watch, book etc. But the digital traces stay relatively invisible for users. In other instances, these digital traces are being made more explicitly observable to users. Let us exemplify. Users of Spotify can see what their friends are listening to right now, Facebook Events lets one perceive how many others who are planning to attend an event and even the simple message that an e-mail was "Sent from my iPhone" exemplifies a consumer *behavior* being digitally disclosed to other individuals. These examples illustrate how the shift from analogue to digital products and services and the resulting digitization of the individual fosters behavior-based digital traces which can be utilized in product design to significantly increase the observability of users' behaviors.

For designers of information systems as well as marketers, this increased observability of user behaviors is intriguing and important given that it is widely accepted that humans can influence each other by means of behavior (Bandura, 1986; Cialdini, 2001). Following this logic, it is perhaps not surprising that several empirical studies have already documented a positive impact from the use of behavior-based information in product design on sales (Chen, Wang, & Xie, 2011), consumer decision making (Cheung, Xiao, & Liu, 2014), online game adoption (Aral & Walker, 2011), link clicks (Tucker & Zhang, 2011), crowdfunding (Thies, Wessel, & Benlian, 2016), software downloads (Duan, Gu, & Whinston, 2009), and music downloads (Salganik & Watts, 2008). Furthermore, it is digital trace data which is already there, generated solely by individuals' purchase or product usage behavior, and thus represents a rich stream of cost-efficient data to potentially be used for marketing-type of purposes (Aral & Walker, 2011).

Although scholars have begun this empirical enquiry into behavior-based information and its use in a marketing and/or product design context, little attention has been allocated to the conceptual aspects of behavior-based information. The few exceptions that do exist have positioned behavior-based information in the context of 'Social Interactions' (Godes et al., 2005), 'Online Social Interactions' (Thies et al., 2016), or 'Customer-to-Customer Interactions' (C2C) (Libai et al., 2010)[1]. Social Interactions take two forms: Opinion-based and behavior-based, where the former is consistently referred to as Word of Mouth (WOM) or Electronic Word of Mouth (eWOM) in the case of digitally communicated opinions. However, while there is a rich literature about the concept of (e)WOM (its definition, types of eWOM, dynamics of impact etc.), the conceptual aspects of behavior-based information haven't been systematically investigated. This is surprising given how recent years' digitization has significantly increased the observability of consumers' behaviors and the extant empirical research demonstrating their profound impact on observers' subsequent choices. The consequence is that knowledge is scattered, the terminology is diverse, and, as we shall show, important conceptual elements and processes have so far been neglected. We argue that this lack of common ground hinders the accumulation of knowledge (Gregor, 2006) at the expense of both scholars and practitioners.

This paper explores behavior-based information and its use in product design. We derive the concept of eWOB based on the literature about Digital Trace Data, Social Interactions, eWOM and extant research on the impact of digitally observable behavior-based information. By extracting central components and themes from these literatures and adapting them to the specific case of behavior-based information we are able to construct a conceptual framework of eWOB and a formal definition of eWOB as "*published accounts of behavior, based on the unobservable digital traces of consumers' behaviors".* Our aim is that this new concept will help advance knowledge about this important phenomenon and guide practitioners in their efforts to design products and services that persuade, inspire, engage, and retain users.

The importance of behaviors

Consumers of today are faced with massive amounts of information about products and services (Godes et al., 2005; Sasaki, Becker, Janssen, & Neel, 2011). Not only has the number of available products vastly expanded due to the rise of the internet and the accompanying virtually unlimited shelf space of online retailers (Duan et

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[1] To simplify, we refer to these almost identical concepts as 'Social Interactions'

al., 2009) but also the number of attributes and specifications about products has seen a sharp increase (Godes et al., 2005). Adding to that, product quality can be difficult to ascertain before purchase in many e-commerce purchase situations (Thies et al., 2016). Given this information overload and information asymmetry, consumers often turn to the either the recommendations and opinions of social others (i.e. eWOM) or the actions taken by social others for guidance in product-related decisions (Duan et al., 2009; Godes et al., 2005; Sasaki et al., 2011; Thies et al., 2016)

While eWOM (in its many forms) in extant literature has been recognized as extremely impactful on many product-related decisions (Zhou & Duan, 2016) a major challenge still remains: generating eWOM requires effort and consumers have limited time for actively expressing their opinions online (King, Racherla, & Bush, 2014). Consequently, it is fair to assume that most people will review or rate only a fraction of the products they purchase and consume. In other words, behaviors outnumber opinions. Against this backdrop, we argue that eWOM, although influential in its own right, represents only a tip of a much larger iceberg of potential social influence that digital products and services can take advantage of. In the digital society of today the many digital behaviors performed by internet users and consequently logged by digital services everyday represent the bottom of that iceberg. Whether it be playing a song on Spotify, reading a book on one's Kindle or booking a hotel on Hotels.com, they all leave digital traces, many of which can be turned into meaningful communicative cues by the particular service without any additional effort required by users. Simply put, the internet has vastly increased the observability of behaviors (Liu, Brass, Lu, & Chen, 2015), in effect turning mere behaviors into "accountable social actions" that are "observable and reportable" (Garfinkel, 1967).

Interestingly, a number of recent empirical studies have actually found that the disclosure of past user behaviors is more impactful than is the disclosure of opinions in the form of eWOM (e.g. Cheung et al., 2014; Thies et al., 2016). However, the use of behavior-based social information in digital products and services is still a topic much less explored than is its conceptual sister, eWOM, both conceptually and empirically (Cheung et al., 2014). Accordingly, in this paper we seek to address the recent calls by, amongst others, Chen et al. (2011), Godes et al. (2005) and Libai et al. (2010) for more research into this area.

Theoretical framework

This paper is situated at the intersection of the Marketing and Information Systems research domains. More specifically, we seek to contribute to the interrelated streams of research on Social Interactions and eWOM as well as the emerging literature about Social Design. This interdisciplinarity is no coincidence. Increasingly, the design of digital products and services is merging with marketing mechanics. A prime example is multi-sided platforms where the importance of integrating marketing mechanics into the core of the product has been recognized as pivotal (Parker, Van Alstyne, & Choudary, 2016). Accordingly, new research problems that require the integration of both research domains arise. One such is the use of behavior-based information in product design. In the following section we offer two complementary perspectives on behavior-based information: behavior-based information as Digital Trace Data and as Social Interactions. Further, we review extant literature on the impact of observable behavior-based information to assess the current state of knowledge and derive three design dimensions.

Digital Trace Data

Behavior-based information can be regarded as an instantiation of 'digital trace data'. Digital trace data is the long trail of data records that get logged when users of digital products or services interact with a digital system. It has been defined as "*records of activity (trace data) undertaken through an online information system (thus, digital)*" (Howison, Wiggins, & Crowston, 2011, p. 769) and also sometimes referred to as 'Digital Footprints' (e.g. Zhao, Binns, Kleek, & Shadbolt, 2016). Driven by the increasingly digital lives of our time, most of us leave innumerable digital traces everyday (Zhao et al., 2016). Some of these traces are intentionally left by users. For example, the act of posting a Facebook post is an action intentionally meant to be disclosed – and thus, leave a digital trace – to a (selected) audience. Similarly, retweets, hyperlinks, and number of Twitter followers have all been described as 'digital traces' (Freelon, 2014), all of which represent examples of observable digital traces that are left with some degree of intentionality.

On the contrary, other digital traces are simply traces of our behaviors that are logged and stored by services and which are unobservable to users. In the case of listening to a song on Spotify (a behavior), Spotify most likely logs a plethora of information about that behavior, e.g. time of day, geographical location, and how many seconds the song was listened to. These data are not left intentionally by the user (a Spotify user is hardly likely to put on a specific song to leave a trace within the system). In fact, one of the defining characteristics of digital trace data is that it is a byproduct of online users' activities (Howison et al., 2011). In this paper, we refer to these unintentionally left digital traces as 'unobservable digital traces' as they are not readily visible to the users despite being stored by the digital system.

The unobservable digital traces might seem mundane. But many digital services nowadays successfully use this type of digital traces of behavior in several ways. One way has been as input into recommendation engines. In such cases the trace itself is still unobservable to the user that generated the trace as well as to other users. Another way to use these digital traces of behavior is to make them observable to users as an integral part of the product experience. Continuing with the music streaming example, Spotify displays which tracks that have been “Recently Played” by particular users, which tracks a user’s Facebook friends are listening to right now, and how many monthly listeners a particular artist has. Here, users’ music listening behaviors are not only logged, but also made observable by the service to users in various ways (synchronous vs. asynchronous, collocated vs. distributed, individual-specific vs. aggregated etc.). It is this particular use of unobservable digital traces to be transformed into observable traces of behavior that we refer to as eWOB.

Social interactions

The concept of ‘Social Interactions’ (SI) encompasses the many different ways information (typically product/company-related) can flow from consumer(s) to consumer(s) and which have the potential to influence the purchase/usage decisions of the receiver(s) of that information (Libai et al., 2010). SI can take two overall forms representing two fundamental ways for consumers to influence each other: opinion-based SI or behavior-based SI (Chen et al., 2011; Cheung et al., 2014; Libai et al., 2010; Thies et al., 2016). The focus of this paper is the behavior-based SI, however in order to fully understand its characteristics and how it fits into the larger picture, we first offer a brief review of the opinion-based SI, which in the literature is unanimously referred to as WOM or eWOM depending on an offline or online setting respectively.

Opinion-based social interactions: A brief introduction to WOM and eWOM

WOM has been said to be one of the most powerful marketing tools, and so old that it precedes marketing as a discipline (Stanislaw, 2015). The early conception of WOM was a one-to-one and face-to-face exchange of information about a product or service (Godes et al., 2005), such as informal “over the backyard fence” conversations (King et al., 2014) and thus a mostly verbal activity (Libai et al., 2010). Empirical studies dating back to the mid twentieth century have proved WOM to be a powerful source of information for consumers and one more important than mass media-style sources of information (Arndt, 1968) amongst others because of its trustworthiness (Cheung & Thadani, 2012; Godes et al., 2005).

With the advent of internet, WOM was extended to also include digitally transmitted consumer-to-consumer messages, i.e. Electronic Word of Mouth (eWOM), often defined as "*any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet*" (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004, p. 39). Although WOM and eWOM share the same fundamental element of consumer-to-consumer transfer of information, eWOM has been recognized to carry a unique set of characteristics facilitated by the internet. For example, eWOM has been said to possess greater speed of diffusion (Cheung & Thadani, 2012; Godes et al., 2005), greater anonymity (Cheung & Thadani, 2012; Godes et al., 2005; King et al., 2014), enhanced volume (King et al., 2014), greater accessibility (Cheung & Thadani, 2012; King et al., 2014), and to be more measurable and thus less open for interpretation (Cheung & Thadani, 2012; King et al., 2014). Arguably, eWOM can take many different forms, e.g. debates on online discussion forums, social media chatter, blogs, and online consumer reviews to name a few (Cheung & Thadani, 2012). In an attempt to integrate extant findings across all of these different types of eWOM Cheung & Thadani (2012) presented an integrative framework of the impact of eWOM. Here, eWOM is depicted as consisting of "Communicators" (i.e. senders of eWOM), "Receivers" (i.e. those exposed to eWOM), "Stimuli" (i.e. the eWOM content), "Contextual factor" (i.e. the medium/channel), and finally the "Impact" (e.g. a change in attitude and/or purchase intention or actual purchase). We find this model to be useful for understanding the fundamental elements of eWOM and we will therefore draw upon it when we derive the concept of eWOB later in this paper.

Behavior-based social interactions

Whereas extant literature generally agrees that SI consists of either opinion- or behavior-based information and that the opinion-based kind is captured by the distinct and well-established concepts of WOM and eWOM, a closer look at the behavior-based type of SI reveals a lack of common concept to capture this second type of (online) SI. This is evident from a number of recent studies that compare and contrast the impact of opinion-based SI to behavior-based SI, especially in digital contexts (e.g. Chen et al., 2011; Cheung et al., 2014; Thies et al., 2016). This attempt to directly compare opinions and behaviors clearly demonstrates an implicit assumption that the two types of SI are different. However, the question then becomes: If the digital disclosure of user behaviors is not eWOM, then what is it? Table 1 provides an overview of some of the various conceptualizations and operationalizations of behavior-based information in studies that contrast opinions and behaviors.

Table 1. Conceptualization of behavior-based information in extant literature

Paper	Type of SI	Conceptualization	Operationalization
Chen et al. (2011)	Opinion	"WOM"	Online reviews
	Behavior	"Observational learning information"	Information about what other customers have ultimately bought after viewing a specific product
Cheung et al. (2014)	Opinion	"eWOM"	Online reviews
	Behavior	"Action-based information"	Self-reported prior purchase (item added to a "buy-list")
Thies et al. (2016)	Opinion	"eWOM"	Comments & Facebook shares
	Behavior	"Popularity information"	Number of previous backers of a crowdfunding project
Libai et al. (2010)	Opinion	"WOM"	N/A (theoretical paper)
	Behavior	"Observational learning"	N/A (theoretical paper)

First, it is evident that there is a lack of a common concept to capture the behavior-based kind of (online) SI. Multiple different concepts are used and such lack of common theoretical ground hinders the effective accumulation of knowledge in a given field (Gregor, 2006; King et al., 2014). Further, the use of the term "*observational learning information*" presupposes that behavior-based information always has an impact (and a specific kind). This is not the case, just as a review (i.e. piece of eWOM) need not always lead to an impact on those exposed to it – it depends on various factors such as the expertise and the trustworthiness of the person crafting the review (Cheung & Thadani, 2012). Such more nuanced mechanisms of behavior-based information are still to be uncovered. Finally, the use of the term "*popularity information*" signals that behavior-based information carries a specific meaning among those exposed to it. This might very well be the actual meaning ascribed to behavior-based information by users. However, to the best of our knowledge, there is currently no evidence that this is the case, and in the case of digital trace data, which we argue behavior-based information is an instantiation of, researchers have generally been warned not to jump to conclusions about how these subtle traces are interpreted by users (Freelon, 2014).

In summary, extant literature suffers from not only a lack of common concept to capture the phenomenon of interest, but the concepts employed also exhibit a somewhat simplified view of the use of behavior-based information. As such, we argue the need for further theorization of this emerging phenomenon. In line with Gregor's (2006) view of the role of theory, we firmly believe that it will help accumulate and advance knowledge in this field as well as enlighten practitioners' use of behavior-based information in products and services.

Extant research on the impact of observable digital behaviors

Observable behaviors and their impact on others is by far a new research topic. It has been extensively studied in offline contexts from both theoretical and empirical perspectives and in various academic disciplines. For example, economists have argued that individuals tend to disregard their own private signals (prior knowledge and intuition) when exposed to the (opposing) choices made by as little as two other people (Bikhchandani, Hirshleifer, & Welch, 1998). Elaborate experiments have been performed by psychologists, such as the "sky-watching experiment" by Milgram, Bickman, & Berkowitz (1969), showing that people are greatly influenced by observing the mere behaviors of others. However, behaviors have been transformed by the widespread digitization of our lives. A wide range of behaviors with little observability in the offline world are now – or at least can easily be made– digitally observable to others. Additionally, much more granular information about individuals' behaviors can be disclosed because of digitization which altogether give rise to new, interesting research questions about the impact of digitally observable behaviors and how firms can work strategically with them. Accordingly, a stream of literature across academic disciplines (but mainly from Information Systems and Marketing) has begun investigating the impact of such digitally observable consumer behaviors which we shall briefly review in the following.

As stated in the introduction, the digital disclosure of behavior-based information has generally been found, across different product categories, to have a significant impact on the subsequent choices of those exposed to it. Further, this impact has also been seen to extend to subsequent offline behaviors (Bond et al., 2012). Considering the more nuanced dynamics of impact we find that the impact, not surprisingly, varies across different empirical contexts and design configurations as can be seen in Table 2 and discussed in the following.

Table 2. Overview of extant literature on the impact of observable digital behaviors and three design dimensions of behavior-based information, derived from extant literature

PAPER	EMPIRICAL CONTEXT	TYPE OF BEHAVIOR	IMPACT FINDINGS	DESIGN CONFIGURATION		
				Place of disclosure	Level of aggregation	Familiarity
Salganik & Watts (2008)	Experiment music website	No. of previous downloads for a song - disclosed on the website	Significant positive impact of behaviors on music downloads; even for songs whose download count had been manipulated high.	Internal	Aggregated	Unknown (anonymous users)
Duan, Gu & Whinston (2009)	CNET (software)	No. of prior downloads for a piece of software - disclosed on CNET.	Significant positive impact of behaviors on software downloads, whereas ratings (opinions) only has impact on less popular products.	Internal	Aggregated	Unknown (anonymous users)
Aral & Walker (2011)	Online gaming	Facebook friends' achievements in online game automatically posted to Facebook.	Modest, but significant, positive impact of behavior disclosure on game adoption. Behaviors are overall more impactful than WOM-style messages because of the high volume and minimal manual effort required	External (Facebook)	Individual-specific (Facebook friends)	Known (Facebook friends)
Chen, Wang & Xie (2011)	Digital cameras on Amazon	Sales rank (based on no. of previous purchases – disclosed on Amazon	Significant positive impact of behaviors on sales. However, if the number of prior purchases is low, the disclosure hereof has neither positive nor negative impact.	Internal	Aggregated	Unknown (anonymous users)
Tucker & Zhang (2011)	Yellow Pages-style website for wedding services	No. of link clicks per vendor – disclosed on the website.	Significant positive impact of behavior disclosure on website traffic. Narrow-appeal vendors gain more website traffic from disclosure of behaviors than do broad-appeal.	Internal	Aggregated	Unknown (anonymous users)
Bond et al. (2012)	Voting	(Self-reported) voting-behavior in US election posted to voters' Facebook pages	Modest but significant positive impact of behaviors on friends' and friends of friends' actual voting behavior and information seeking. Impact largest among close ties.	External (Facebook)	Individual-specific & aggregated	Known (friends) & unknown
Cheung, Xiao & Lui (2014)	Asian beauty forum	Prior purchases of beauty products - disclosed on users' profile pages.	Significant positive impact of behaviors in terms of influencing purchase decisions. Behaviors are found more impactful than eWOM (opinions)	Internal	Individual-specific	Semi-known (community members)
Bapna & Umyarov (2015)	Last.fm (music streaming)	Users' status as premium subscriber is disclosed on users' profile pages	Significant positive impact of behaviors on purchases of premium subscriptions. Impact largest on users with small number of friends.	Internal	Individual-specific	Most likely both known & unknown (friends & community members)
Thies, Wessel & Benlian (2016)	Indiegogo (crowdfunding)	No. of previous backers for a campaign – disclosed on Indigogo	Significant positive impact of behaviors on funding decisions. However, the impact decays faster than that of eWOM.	Internal	Aggregated	Unknown (anonymous users)

Chen et al. (2011) investigated how the volume of prior purchases impacted sales. Drawing on the theme of 'valence' in the eWOM literature they refer to "*positive*" vs. "*negative*" "*observational learning (OL) information*" (operationalized as a high vs. low purchase percentage respectively of a given digital camera).

Somewhat in contrast to the typical empirical pattern found in research on eWOM valence, they found that that the existence of "*positive OL information*" significantly impacts sales positively while "*negative OL information*" does not have a significant negative impact. This finding indicates that vendors can favorably disclose prior purchases for both broad-appeal products and niche products without hurting the latter. On a related note, Tucker & Zhang (2011) found that narrow-appeal vendors actually seem to benefit more from what they term "popularity information" operationalized as number of clicks a website had received. They conducted a natural experiment on a yellow pages-style website with links to providers of wedding services and found that vendors with a narrow target market (referred to as "narrow appeal" and defined by population size in vendor's town) saw a larger impact of disclosing behavior-based information than did the broad-appeal vendors.

Moreover, the number of connections a user has also seems to matter for the impact. Bapna & Umyarov (2015) applied a network perspective in their investigation of peer-to-peer influence in the case of premium subscriptions to the music streaming Last.fm. They found that those users with a low number of connections on Last.fm were more likely to be influenced by information about whom of their Last.fm connections had purchased a premium subscription than were users with a high number of connections. The logic here is that if a user only has 10 connections, he/she will more easily notice information about each of his/her connections than will a user with 1000 connections (Bapna & Umyarov, 2015). Further, it might also look more convincing when 5 out of 10 of one's connections has signed up for a premium subscription than if 5 out of one's 1000 connections have done so.

Additionally, impact of observable behaviors varies over time. Thies et al. (2016) compared the impact of eWOM and "*popularity information*" in crowdfunding (operationalized as number of previous backers of a given project). They found that although "popularity information" had an overall larger impact than did eWOM, the effect diminishes relatively quickly compared to that of eWOM. Relatedly, Salganik & Watts (2008) performed an experiment in an online music context where less popular songs (i.e. with a low number of actual downloads) were manipulated to look like popular songs (i.e. with a high number of disclosed downloads). This manipulation had a significant immediate impact resulting in an increase in downloads of the falsely popular songs. However, over time the effect wore off and the "true" popular songs regained their popularity, indicating that although clear bandwagon-type of mechanisms exist, consumers do not under all circumstances blindly follow the lead of others.

Further, some researchers have taken their point of departure in the eWOM literature and have made direct comparisons between the impact of eWOM (opinions) and behavior-based information. Accordingly, Cheung et al. (2014) directly compared the effect on consumer decision making of "*opinion-based social information*" (operationalized as peer consumer reviews, i.e. a common type of eWOM) to that of "*action-based social information*" described as "*publicly observable online social information about other consumers' actions*" (p. 51) and operationalized as users' self-reported past purchases. Based on an analysis of a large dataset from an online beauty community, they find that the behavior-based information is more influential than the opinion-based. The same main effect was found by Thies, Wessel, & Benlian (2016) in the context of crowdfunding. Opposingly, Aral & Walker (2011) investigated how users' achievements (i.e. behaviors) in an online game which were automatically shared to Facebook (i.e. outside of the platform where the behavior actually took place) impacted product adoption relative to personalized invitations from existing users to peers (comparable to eWOM). Interestingly, they found that although the personalized invitations had a larger impact *per impression* the automatically disclosed behavior-based information was overall more impactful because of the sheer volume. This highlights what seems to be one of the crucial differences between opinion-based information (eWOM) and behavior-based information: That consumers' behaviors are plentiful and if properly enabled by technology, they can be disclosed in ways that require far less effort from the consumer than the task of forming *and* expressing an opinion.

Summarizing on the above, it is evident that the disclosure past of user behavior has been found to significantly affect other users' choices and behaviors and in some cases even more so than the disclosure of users' opinions (Cheung et al., 2014; Duan et al., 2009; Thies et al., 2016). Further, the impact is moderated by factors such as tie strength (Bond et al., 2012), total amount of ties of a user (Bapna & Umyarov, 2015), impact over time (Thies et al., 2016), size of potential market for the product (narrow vs. broad appeal) (Tucker & Zhang, 2011), and user expertise (Cheung et al., 2014). However, what is also evident from the many empirical cases studied is that behavior-based information can be displayed in digital interfaces in many different ways. Simply put, different designs can be (and are being) used which makes it hard to directly compare the findings of the current literature.

This leads us to an important last point about behavior-based information, namely that there is a substantial element of design involved in the use of behavior-based information. Unlike its sister concept of eWOM, digital behaviors are not made observable to a broad public by the individual user. Rather, it is dependent on the platform where the behavioral trace was recorded. A deliberate design decision must be made to use the digital trace of behavior and transform it into some meaningful piece of information for the observing users. Without design it simply does not come into existence and an opportunity is lost for using behavior-based information strategically to influence customer choices (Duan et al., 2009). Accordingly, and building on Godes et al.'s (2005) assertion that "*at least some of the social interaction effects are partially within the firm's control*" (p. 415), a particular focus on how to design 'viral' or 'social' products has emerged (Aral, Dellarocas, & Godes, 2013; Aral & Walker, 2011; Bapna & Umyarov, 2015; Dou, Niculescu, & Wu, 2013). Here, researchers focus on how social elements (including, but not restricted to, behavior-based information) can be incorporated into the product design to stimulate product adoption, customer engagement, and retaining customers (Bapna & Umyarov, 2015). In line with this design-driven way of thinking strategically about the use of behavior-based information, we argue that the empirical cases investigated in current literature represent at least three overall dimensions of how behavior-based information can be integrated into product design: Place of disclosure, Level of aggregation and Familiarity, as depicted in Table 2.

First, we notice how behaviors are disclosed either within the platform where it was generated, e.g. a user's purchase of a premium subscription to Last.fm is displayed on the user profile within Last.fm (Bapna & Umyarov, 2015) which we shall denote *Internal disclosure*. On the other hand, behaviors can be disclosed to another platform, e.g. Facebook in the case of Aral & Walker (2011) which we refer to as *External disclosure*. By far the most common place of disclosure in extant research is the *internal* which underlines the tendency for marketing mechanics to be integrated into the product. Second, the element of *aggregation* denotes the use of either aggregated data about behaviors ("*100 people have backed this project*" in the case of Thies et al. (2016)) vs. behaviors of specific individuals (e.g. subscription purchases made by specific users, cf. Bapna & Umyarov (2015)). These individuals need not be known to the sender though, which brings us to the third dimension, *familiarity*. Individuals can be strangers (cf. Chen et al. (2011)), fellow community members one has met online (cf. Cheung et al. (2014)), or they can be close ties, also known from the offline world (cf. Aral & Walker, 2011; Bond et al., 2012).

Table 2 does not constitute an exhaustive design framework of the use of behavior-based information in product design as the examples are drawn from the emerging literature on the phenomena. Rather, we seek to offer a high-level overview of the various possible design paths that designers of information systems can take when taking advantage of behavior-based digital traces. As such, the design dimensions laid out aim to not only provide strategic guidance for practitioners but also to function as a framework for researchers to better articulate the differences in the strategic use of behavior-based information and to determine where comparisons across studies can or cannot reasonably be made, and finally identify avenues for future research including optimal design configurations.

Deriving the concept of eWOB

The previous section laid out the theoretical foundations for the concept of eWOB. In the following section, we will use this foundation to derive the concept of eWOB which allows us to arrive at the definition of eWOB as being "*published accounts of behavior, based on the unobservable digital traces of consumers' behaviors*".

Behaviors in a Social Interactions context

In the previous section we saw how interpersonal influence stemming from observing the behaviors of others can be viewed as one of the two overall types of Social Interactions (SI). Although there has been an increasing interest among researchers to investigate the impact of observable behavior-based information extant literature on this topic lacks a shared terminology from which to consolidate knowledge and a stronger conceptualization to understand the unique characteristics of observable behavior-based information and how it differs from the related concept of eWOM. In the following section we will draw on the *three facets of SI* presented by Godes et al. (2005) to illustrate (a) key elements of behavior-based information, (b) when it actually becomes eWOB, and (c) how eWOB differs from eWOM.

SI possess three essential facets (Godes et al., 2005): *Channel*, *Content*, and *Impact* as illustrated in Figure 1. In the case of eWOM (i.e. opinions) the *channel* is the medium in which an opinion is communicated through, for example a review platform such as Tripadvisor. The *content* is then the (opinion-based) information passed on, i.e. the actual instantiation of eWOM. In the case of Tripadvisor this could be a review of a hotel. Finally, the *impact* is the ultimate effect on those exposed to the eWOM, e.g. a change in attitude among prospective customers, the forming of a purchase intention (or the opposite) or even an actual purchase.

Social Interaction Element	Exemplification
Channel	Review site, blog etc.
Content	eWOM
Impact	Change in attitude and/or behavior

Figure 1. Godes et al.'s (2005) three facets of Social Interactions

This three-tier model is useful for describing the main components of the opinion-based kind of SI. However, to fully demonstrate how what we refer to as eWOB fits into the context of SI and how it differs from eWOM we need to adapt the model with a number of additional facets (Figure 2).

Social Interaction Element	Exemplification	
Trigger	Opinion	Behavior
Trace	N/A	Unobservable digital trace data
Channel	Review site, blog etc.	Product interface, Facebook etc.
Agent	Consumer	Platform (product/Service)
Content	eWOM	eWOB
Potential explanatory mechanism of impact	Social influence	Observational learning
Impact	Change in attitude and/or behavior	Change in attitude and/or behavior

Figure 2. Social Interactions expanded

First, the three-tier model disregards what comes before the instantiation of the actual *content*. At the most fundamental level, an opinion is really just a subjective assessment inside one's head. It leaves no trace until it is communicated through a channel and then the opinion becomes a piece of communication. The same cannot be said about digital behaviors. Most, if not all, digital behaviors leave a trace inside an information system (Howison et al., 2011). These traces are unobservable to the users of the information system. Accordingly, to discern between the opinion/behavior itself and its instantiation as *content* we add the element of *Trigger*, being either an opinion or a behavior. Second, we add the element of *Trace* to capture the traces left before the opinion/behavior takes the form of actual *content*.

Third, we add the element of *Agent*, describing the primary agent involved in turning mere opinions and behaviors into actual communicative *content*. In eWOM, the *content* is created by the consumer (cf. for example Cheung & Thadani (2012); King et al. (2014)). The *channel* might help creating an overall format for how the opinion is being transformed into actual *content*, for example the possibility to add stars to a review. But the consumer is the primary *agent* responsible for turning opinions into eWOM content. On the contrary, with behaviors the primary *agent* is the platform where the behavior took place which in most, but not all, cases will also be the *channel* that communicates the eWOB. Let us elaborate. For a digital trace to become actual *content* (i.e. eWOB), the platform that captured the digital trace acts as the *agent* that turns the trace into *content* with communicative value that is observable to other users. It is not the individual user who does so. The user might at some point give his/her one-time permission for the platform to disclose his/her usage behaviors to his/her connections (as the Facebook-integration used in Aral & Walker (2011) requires), but it is not a decision that needs to be taken for each piece of content. Further, in cases where the individual's behavior is aggregated with other users' (as in the case of e.g. Chen et al. (2011); Thies et al. (2016); Tucker & Zhang (2011)), the individual user will not at all be actively involved in the disclosure.

Fourth, we add the element of *Potential Explanatory Mechanism of Impact*. This element is useful for understanding one of the key confusions in extant literature about behavior-based information. Referring back to Godes et al.'s (2005) original three facets of SI, we find the *impact* to be the "*ultimate effect*" on those exposed to SI, e.g. sales. Given the human-to-human nature of SI it is reasonable to assume that the final *impact* is a result of social influence (acknowledging that social influence also has many facets) which represents what we term the *potential explanatory mechanism of impact*. In the case of behavior-based information we would expect the *impact* to be a result of the particular type of social influence, namely Observational Learning (Bandura, 1986; Bikhchandani et al., 1998), given the widespread use of Observational Learning as a theoretical lens for the impact of observable behaviors (e.g. Chen, Wang, & Xie, 2011; Libai et al., 2010). However, turning to the extant literature that seeks to directly compare the impact of opinion-based and behavior-based information, we notice how ”observational learning" is used to describe the behavior-based *content*, whereas the opinion-based *content* is referred to as 'eWOM'. Clearly, there is a conceptual misalignment where the term used to describe the *content* is also the *potential explanatory mechanism of impact*. Further, as seen in Table 1 "action-based information" has also been used as a term to denote the *content* level (e.g. Cheung et al., 2014). However, this effectively is comparable to the *Trigger* level in this framework.

In conclusion, we argue that Godes et al.'s (2005) three facets of SI provide a good foundation for conceptual alignment of eWOM and eWOB but that several new facets have to be introduced to encompass the particular characteristics of eWOB. Further, we identified two central aspects that differentiate eWOB from eWOM: (a) the ability to leave unobservable *traces*, and (b) the *agent* driving the transformation of the initial *trigger* into actual (observable) *content*.

Behavior-based information in an eWOM context

In this section we will draw on the integrative framework of the impact of eWOM communication developed by Cheung & Thadani (2012) to further illustrate how eWOB differs from the related concept of eWOM. The Cheung & Thadani (2012) framework was chosen as it provides a comprehensive overview of the main components of eWOM from both a supply- and demand-side perspective and in greater detail than the SI framework used in the previous section. To better highlight the dynamics of eWOM communication we have slightly modified the original framework to highlight the process of eWOM communication, and additionally also simplified the *Response* category. Figure 3 illustrates this slightly simplified version of the framework.

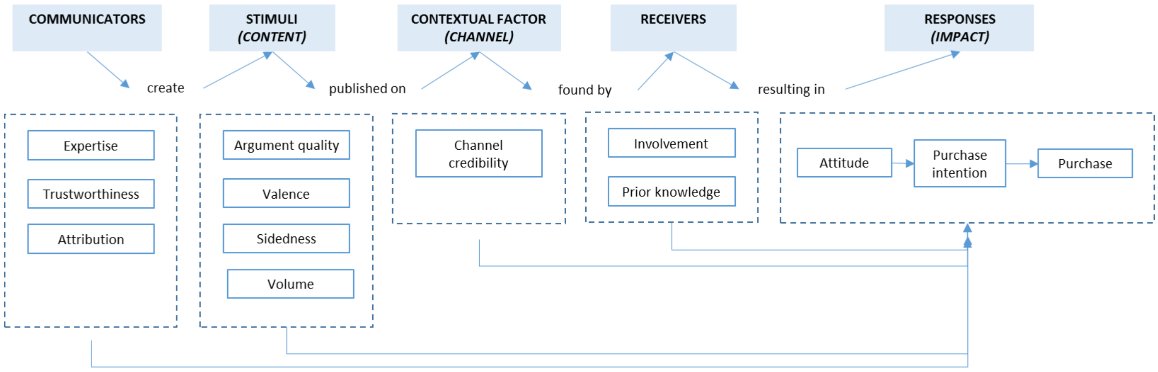

Figure 3. Integrative framework for the impact of eWOM communication, adapted from Cheung & Thadani (2012)

The basic logic of the framework is that an individual (*Communicator*) creates a piece of eWOM *Stimuli* (equivalent to *content* in the SI framework), e.g. a review on Amazon. This is now made available to other individuals by a *Channel*[2]. The *Stimuli* is now seen by a *Receiver* or a multitude of hereof. Finally, this might lead to a *Response* (equivalent to *impact* in the SI framework), which can range from a slight change in attitude to actual purchase. Related to both the *communicators*, the *content*, the *channel*, and the *receivers* are a number of variables that directly affect or moderate the *impact*, shown in the boxes with dotted lines in Figure 3. We will now present a revised version of the above framework which outlines the basic elements and dynamics of eWOB. By taking our point of departure in an established model of eWOM, we hope to be able to highlight differences and similarities between the two interrelated concepts.

[2] Cheung & Thadani's original term for this element was 'Contextual Factor', however it basically describes the channel/platform on which the eWOM was published, and thus we will refer to it as Channel which also aligns it with the SI framework

As can be seen from Figure 4, our framework of eWOB shares many of the same overall elements with eWOM. In both cases, a piece of *content* is transferred from *communicators* to *receivers* through some *channel*, which in the end might lead to an *impact* on the *receiver*. However, a closer look reveals several new elements (marked with thick line in Figure 4) as well as the deletion of elements deemed irrelevant for eWOB.

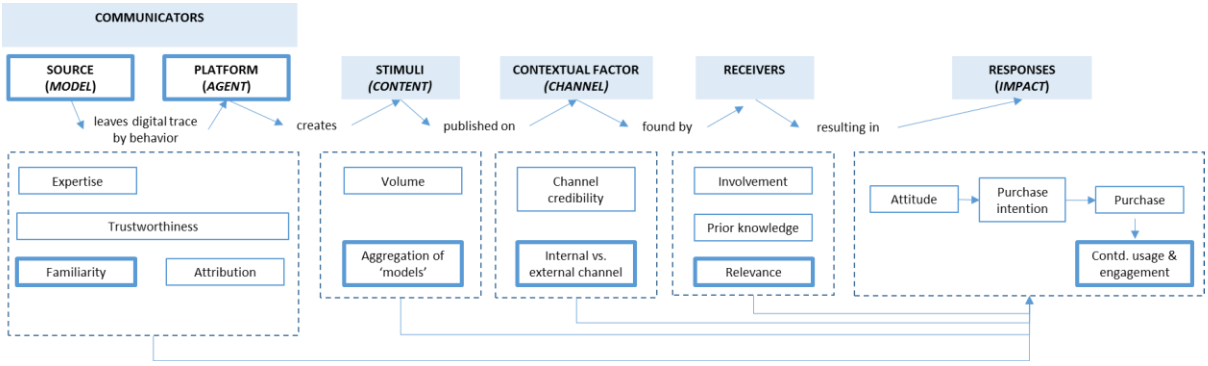

Figure 4. Framework for eWOB

First, the *communicators* consist of two sub-elements: *source* (model) and *platform* (agent). Referring to digital traces and social interactions, a special characteristic of digital behaviors is that they leave digital traces, often unintentionally, by the user of the system. We call the person leaving this behavior-based digital trace the *Source* and drawing on the terminology from Observational Learning, we say that the *source's* behavior is being "modeled" when made observable to others (Bandura, 1986). However, someone must decide to disclose that behavior (an *agent*). Unlike eWOM where the *agent* is the consumer him/herself, in the case of eWOB the *agent* is not the *source* but rather the *platform* on which the trace was generated (which often, but not always, is identical to the *channel* that discloses the behavior). Here, a deliberate design decision must be made to make the digital trace observable and in which way(s). Drawing on mechanisms known from Observational Learning (Bandura, 1986) we should also in the case of behavior-based information expect a number of elements related to the *communicators* influence the final *impact*: The expertise of the *source* within the given area, the trustworthiness of both the *source* and the *platform* and the motives attributed to the platform for disclosing the behavior-based information as eWOB. However, these are not empirically demonstrated yet and further empirical research is needed in this regard. Finally, drawing on extant research about the impact of behavior-based information and the three design dimensions derived from that we add the element of *Familiarity* to describe the strength of tie between the *source* and the *receiver* (known vs. unknown, weak vs. strong tie). Here, prior empirical research suggests that behaviors spread faster through strong ties (Bond et al., 2012) but this might very well vary by product category and thus is an area for further empirical validation.

Second, the behavior is turned into actual *content*. Here, we see in the original framework by Cheung & Thadani (2012) that the *argument quality*, the *valence*, and *sidedness* (direction of valence) are all expected to influence the *impact*. However, we argue that in the case of eWOB these elements are hardly assessable. The simple reason is that the disclosure of behaviors – as opposed to opinions - is a subtler way of communicating (Chen et al., 2011) . It is by nature a rather neutral account of behaviors and in our view thus not possible to assess neither *argument quality, valence* (positive/negative), nor *sidedness*. While some studies have used the volume of behaviors as a proxy for its valence (Chen et al. (2011) reported a low number of prior purchases as "*negative observational learning information*") we argue that the use of volume to assess valence should be employed with caution, if at all, as it really depends on the characteristics of the receiver and his/her reference group. One might very well imagine a scenario where more niche-orientated consumers actively try to steer away from the bestseller products and thus towards products that seem less popular, measured by sales. In such a scenario, a high number or prior purchases would actually be perceived as negative valence among this niche-segment. But if the same product is (also) the most purchased/used within the niche-orientated customer's own reference group (Shibutani, 1955) it might be perceived as positive. This goes to show that the categorization of behavior-based information into 'positive' and 'negative' might not be as simple as it looks on the surface. For these reasons the three elements of *argument quality*, *valence,* and *sidedness* were excluded from the eWOB framework. Further empirical investigation is clearly needed in this area in order to shed light on these more detailed mechanics of eWOB. Finally, drawing on the previously discussed three design dimensions that were derived from empirical cases in extant literature, we add the element of *aggregation* to describe whether *communicators* are presented at an aggregated level or as individuals or both.

Third, the content must be disclosed through some *channel* (referred to as 'platform' in Cheung & Thadani's framework), and the nature of that *channel* might influence the final impact. Amazon might be perceived more credible than a relatively unknown review platform, and thus the impact of the reviews (*content*) will be affected by the *channel*. Similarly, we see no reason not to believe that the impact of eWOB content also varies across different *channels*, however needs to be empirically validated by future research. Further, in the case of eWOB the *channel* can– but need not – be the same as the *platform*. If the *platform* where the behavior took place is also the place where the *content* is published (e.g. a behavior on Indiegogo gets disclosed on Indiegogo as in the case of Thies et al. (2016)), that is an example of *internal disclosure*. Conversely, if the behavior on Indiegogo is published on Facebook, then we refer to that as *external disclosure*. Thus, we add this last of our three design dimensions to the eWOB framework. Whether the *external* or *internal* type of disclosure is the more impactful is premature to conclude based on extant empirical research. However, we argue that – all things being equal - the observer is reached in a more relevant context in the case of *internal disclosure* (an Indiegogo user is presented with information about the behaviors of other users on Indiegogo while using Indiegogo herself), whereas observers in the case of *external disclosure* might be preoccupied with tasks that has nothing to do with the behavior being disclosed to them (a Facebook user is presented with a story about her friend's backing of a project on Indiegogo – in the midst of reading the news on Facebook and watching friends' baby photos). Drawing again on Observational Learning theory, we should thus expect the *internal disclosure* to have a greater impact, as behaviors that are considered more personally relevant have greater impact on the observer(s) (Bandura, 1986).

Fourth, in the case of eWOM the *involvement* and *prior knowledge* of the receiver are important aspects for the final *impact.* This makes sense as the use of eWOM is typically depicted in the literature as an active information-seeking process (mainly a 'pull' type of information) from the side of the receiver (e.g. Bartikowski & Walsh, 2014; Chang & Wu, 2014; Cheung & Thadani, 2012; Daugherty & Hoffman, 2014; Fu, Ju, & Hsu, 2015; Goodrich & de Mooij, 2013; King et al., 2014). Therefore, the more involved the receiver is, the greater the expected impact will be. However, in the case of eWOB we argue that the receiver is less likely to be actively seeking this type of information (mainly a 'push' type of information) and consequently the contextual relevance for the receiver of that information is more important than in the case of eWOM. Therefore, we add *Relevance* to the framework.

Finally, we add a new type of *impact* to our eWOB framework, namely *Continued usage & engagement*. Clearly, some types of eWOB are – just like eWOM – designed with the impact goal of persuading users to complete a purchase. In other cases, though, we notice how the function of eWOB seems to be more a matter of stimulating continued usage and engagement. For example, being able to observe on Spotify what friends are listening to right now is clearly not designed to persuade one into a purchase, as the user has already signed up for Spotify. Rather, it is most likely implemented to create a sense of community and/or provide inspiration for what to listen to and/or simply confirming the user in his/her choice of Spotify through showing the presence of social others, all of which stimulate *continued usage and engagement*. Accordingly, researchers assessing the impact of eWOB should in future research also consider the impact beyond the purchase stage.

To sum up, our framework of eWOB illustrates that eWOB differs from eWOM in a number of central aspects. Arguably, the most important difference is the duality of the *communicators* consisting of both a *source* and a *platform.* But also, the more neutral nature of eWOB (being purely behavior-based) is a clear difference from eWOM, where *valence*, *sidedness*, and *argument* quality are traditionally central themes of analysis but difficult, if not impossible, to assess in the case of eWOB. Finally, with eWOB the desired *impact* might very well be not only on sales but also on *continued usage and engagement* due to the subtler nature of eWOB.

Discussion

This paper is motivated by the increased observability of consumer behaviors enabled by the widespread digitization of individuals' daily lives. Building on the foundations of Digital Trace Data, Social Interactions, and eWOM, we have derived the concept of eWOB defined as *published accounts of behavior, based on the unobservable digital traces of consumers' behaviors* to fill in a conceptual gap in extant literature about Social Interactions and eWOM. Our definition highlights that eWOB is content based on unobservable digital traces that are generated solely by user behavior. As a consequence, eWOB is truly design-driven and the platform (i.e. digital product/service) is the primary agent responsible for turning unobservable digital traces into actual communication that is observable to others. From the perspective of the receiver this also entails a duality in terms of who the communicator is. The central aspect of digital trace data and the active role of the platform further means that it is not to be considered eWOB when a consumer actively creates a Facebook post with a photo of him/her unboxing a new iPhone. This is in its core an expression of product-related *behavior* (signaling a recent purchase of the iPhone), however we consider it to be eWOM as it is actively created by the user and not as a result of prior logged behavior. Finally, eWOB, the term itself deserves elaboration. At first glance, the use of '*Word*' might seem to limit the concept to written communication. However, the '*Word*' should be interpreted in a broader context that denotes the *communication* of behaviors. This is no different from the term eWOM, where it is widely recognized that eWOM can take other forms than verbal/written communication, e.g. the existence of 'visual eWOM' (King et al., 2014).

Contributions

This research aims to contribute to theory by offering conceptual clarification and a detailed account of the dynamics and characteristics of an emerging phenomenon in the interrelated literatures of Social Interactions and eWOM, spanning across the Information Systems and Marketing disciplines. Specifically, our research seeks to address several important conceptual gaps in extant literature. First, although several empirical studies exist on the topic of behavior-based information, this literature has so far treated behavior-based information as relatively homogenous. However, as we have shown, it can take many different forms which to a large degree is dependent on design. Second, although extant literature has indeed made direct comparisons of the impact of behavior-based information and opinion-based information (eWOM), we have addressed a conceptual gap in terms of how the two distinguish themselves from each other and what the unique characteristics and processes of eWOB are. Accordingly, we encourage researchers to use our proposed conceptual framework as a tool to point out opportunities for future research and the structuring hereof; for example by investigating the impact of different design configurations or the role of moderating factors such as trustworthiness, engagement etc. Given that extant literature is still conceptually at an early stage, many opportunities exist for such comparative empirical studies. Moreover, our research adds to the current understanding of 'social/viral product design' (Aral & Walker, 2011; Bapna & Umyarov, 2015), by expanding our conceptual and design-specific knowledge of a specific sub-component of social design, namely the use of behavior-based information in the form of eWOB.

Finally, our research highlights the design-aspect of eWOB and thus the active role of the platform in the creation of eWOB. As current empirical research has demonstrated significant positive impacts of eWOB, we urge practitioners to consider this exciting opportunity to actively use behavior-based information in product design to persuade, inspire, engage, and retain users. With the proposed conceptual framework, we seek to provide system designers not only with an overview of both the design opportunities but also the central mechanisms of eWOB. Much akin to how a manager will benefit from knowing different kinds of organizational structures (for example a matrix, functional, or divisional structure), we hope that the conceptual framework can act as a roadmap for system designers and facilitate a strategic use of behavior-based information in the form of eWOB. Only by being aware of the conceptual underpinnings of a phenomenon and its core components can one instrumentally work with it beyond trial and error.

Open research questions & future research directions

Hopefully, our introduction of eWOB has brought about conceptual clarity around the digitally observable behaviors of consumers and how it fits into the larger context of Social Interactions and complements the well-established concept of eWOM. However, the introduction of a new concept also gives rise to new intriguing research questions that are ripe for further research. First, the issue of product category is critical in a number of ways. While we argue a broad possible use of eWOB, obviously there are types of products simply not suitable for eWOB activities. On the one hand, it is not difficult to imagine products where users will prefer to leave no observable traces about their behaviors and where it would also be considered awkward to be receiver of that information, an obvious example – especially at the individual-specific level - is adult movies. In other cases, the behaviors may simply be too mundane to disclose at least at the individual-specific level. Does one want to know the specific brand of detergent that one's friend has purchased in an online supermarket? The answer will depend on the context and the way the eWOB is presented. Finally, in some product categories consumers will actually try to diverge from the choices made by their immediate surroundings. Fashion is one such example. Here, consumers might actively try to steer away from products purchased by close friends to avoid looking too similar. Thus, eWOB can actually have an inverse impact guiding consumers to what *not* to buy. Further, although the eWOB in such instances might not stimulate product diffusion it could actually be imagined having a relational effect, i.e. being able to the see fashion purchases of significant others might stimulate conversation between peers. Accordingly, we argue that eWOB could potentially also stimulate the basic human need for relatedness (Ryan & Deci, 2017). This relational role of eWOB is to the best of our knowledge completely absent from extant literature and represents an exciting new research topic. Additionally, the nature of the product (complexity and ability to assess its fit and usefulness before purchase) is relevant for the role of eWOB. Consider the category of digital cameras. Here, most users do extensive research before making an actual purchase and thus an observable purchase might signal more than a purchase behavior but rather the culmination of a thorough information-seeking process. In such cases, we should expect eWOB to signal to observers something close to an opinion. In other cases, e.g. movie watching, being able to observe that a friend has watched a specific movie will probably carry much less information to the observer as a movie can only truly be assessed *after* having watched it. If we can observe that the friend has watched it *several* times, we might be able to infer some more informational value from that but such comparisons are relevant to explore in future research.

Next, our conceptualization of eWOB and the review of extant empirical research in this domain give rise to several design-related questions. For instance, how does the impact of eWOB vary with the degree of customization? Cheung et al. (2014) suggested that customization of eWOB can be necessary to avoid information overload, but are certain product categories more suitable for customization? Further, research should explore and compare how various ways of presenting eWOB affects impact e.g. eWOB presented at the individual-specific level vs. at an aggregated level; eWOB from strangers vs. known people; from strong vs. weak ties etc. as well as the impact of internal vs. external disclosure of eWOB. Building on that, we should notice that the design dimensions presented in this paper are not exhaustive as they are primarily built on the cases used in extant empirical research. Moreover, while the focus of this paper as well as prior research in this domain has been on the disclosure of behaviors to *others*, it is not far-fetched to believe that a *Source-to-Source* information flow of eWOB can actually present valuable information for users similar to the design mechanisms of the ‘quantified self’ movement such self-monitoring (Snyder, 1987) and as known from Observational Learning (Bandura, 1986). A concrete example is when Spotify at the end of each year presents users with their own most listened to songs for that year.

Finally, two pressing issues related to the user perspective need to be explored. First, researchers are urged to follow the call by Freelon (2014) and apply a user-perspective to the interpretation of eWOB. Researchers cannot simply assume that eWOB is solely interpreted by users as an expression of popularity. It might also have other important interpretations and functions such as the relation-supporting role suggested in the above. Last, but absolutely not least, the element of ethics and trust requires further research. At the time of writing, eWOB seems to be completely unregulated with little opportunity for consumers to assess whether the information presented to them is real, distorted, or simply fake. Especially relevant here is eWOB presented at an aggregated level or eWOB from strangers. As Salganik & Watts (2008) has shown, human beings can easily be manipulated by such information. Consequently, just as the eWOM literature has dealt with fake reviews and trust (e.g. Chiou, Chang, Mezzour, Perrig, & Sun, 2009; Furner, Zinko, & Robert A., 2016; Zhang, Zhou, Kehoe, & Kilic, 2016), so should future research about eWOB.

In closure, the phenomenon of eWOB is an exciting new area where marketing seems to merge with the design of digital products and services. Several empirical studies have shown the significant impact of eWOB but many areas are still underexplored. We thus encourage scholars and practitioners alike to engage in eWOB research and activities to further advance knowledge in this field.

References

Aral, S., Dellarocas, C., & Godes, D. (2013). Introduction to the Special Issue —Social Media and Business Transformation: A Framework for Research. *Information Systems Research*, *24*(1), 3–13. http://doi.org/10.1287/isre.1120.0470

Aral, S., & Walker, D. (2011). Creating Social Contagion Through Viral Product Design: A Randomized Trial of Peer Influence in Networks. *Management Science*, *57*(9), 1623–1639.

Arndt, J. (1968). Selective Processes in Word of Mouth. *Journal of Advertising Research*, *8*(3), 19–22.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice-Hall.

Bapna, R., & Umyarov, A. (2015). Do Your Online Friends Make You Pay? A Randomized Field Experiment on Peer Influence in Online Social Networks. *Management Science*, *61*(8), 1902–1920.

Bartikowski, B., & Walsh, G. (2014). Attitude contagion in consumer opinion platforms: posters and lurkers. *Electronic Markets*, *24*(3), 207–217. http://doi.org/10.1007/s12525-013-0149-z

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1998). Learning from the Behavior of Others: Conformity, Fads and Informational Cascades. *Journal of Economic Perspectives*, *12*(3), 151–170.

Bond, R. M., Fariss, C. J., Jones, J. J., Kramer, A. D. I., Marlow, C., Settle, J. E., & Fowler, J. H. (2012). A 61-million-person experiment in social influence and political mobilization. *Nature*, *489*(7415), 295–298.

Chang, H. H., & Wu, L. H. (2014). An examination of negative e-WOM adoption: Brand commitment as a moderator. *Decision Support Systems*, *59*(1), 206–218. http://doi.org/10.1016/j.dss.2013.11.008

Chen, Y., Wang, Q., & Xie, J. (2011). Online Social Interactions: A Natural Experiment on Word of Mouth Versus Observational Learning. *Journal of Marketing Research*, *48*(2), 238–254.

Cheung, C. M. K., & Thadani, D. R. (2012). The impact of electronic word-of-mouth communication: A literature analysis and integrative model. *Decision Support Systems*, *54*(1), 461–470. http://doi.org/10.1016/j.dss.2012.06.008

Cheung, C. M. K., Xiao, B. S., & Liu, I. L. B. (2014). Do actions speak louder than voices? The signaling role of social information cues in influencing consumer purchase decisions. *Decision Support Systems*, *65*, 50–58.

Chiou, S.-Y., Chang, S.-Y., Mezzour, G., Perrig, A., & Sun, H.-M. (2009). A Trustable Reputation Scheme

Based on Private Relationships. In *2009 International Conference on Advances in Social Network Analysis and Mining* (pp. 19–24). IEEE. http://doi.org/10.1109/ASONAM.2009.8

Cialdini, R. B. (2001). Harnessing the Science of Persuasion. *Harvard Business Review*, *79*(9), 72–81.

Daugherty, T., & Hoffman, E. (2014). eWOM and the importance of capturing consumer attention within social media. *Journal of Marketing Communications*, *20*(1–2), 82–102. http://doi.org/10.1080/13527266.2013.797764

Dou, Y., Niculescu, M. F., & Wu, D. J. (2013). Engineering Optimal Network Effects via Social Media Features and Seeding in Markets for Digital Goods and Services. *Information Systems Research*, *24*(1), 164–185.

Duan, W., Gu, B., & Whinston, A. B. (2009). INFORMATIONAL CASCADES AND SOFTWARE ADOPTION ON THE INTERNET: AN EMPIRICAL INVESTIGATION. *MIS Quarterly*, *33*(1), 23–48.

Freelon, D. (2014). On the Interpretation of Digital Trace Data in Communication and Social Computing Research. *Journal of Broadcasting & Electronic Media*, *58*(1), 59–75. http://doi.org/10.1080/08838151.2013.875018

Fu, J.-R., Ju, P.-H., & Hsu, C.-W. (2015). Understanding why consumers engage in electronic word-of-mouth communication: Perspectives from theory of planned behavior and justice theory. *Electronic Commerce Research and Applications*, *14*(6), 616–630. http://doi.org/10.1016/j.elerap.2015.09.003

Furner, C., Zinko, P., & Robert A. (2016). The influence of information overload on the development of trust and purchase intention based on online product reviews in a mobile vs. web environment: an empirical investigation. *Electronic Markets*. http://doi.org/DOI 10.1007/s12525-016-0233-2

Garfinkel, H. (1967). *Studies in Ethnomethodology*. Englewood Cliffs, NJ: Prentice-Hall.

Godes, D., Mayzlin, D., Chen, Y., Das, S., Mit, C. D., Pfeiffer, B., & Shi, M. (2005). The Firm's Management of Social Interactions. *Marketing Letters*, *16*(3/4), 415–428.

Goodrich, K., & de Mooij, M. (2013). How "social" are social media? A cross-cultural comparison of online and offline purchase decision influences. *Journal of Marketing Communications*, *20*(2), 1–14. http://doi.org/10.1080/13527266.2013.797773

Gregor, S. (2006). The Nature of Theory in Information Systems. *MIS Quarterly*, *30*(3), 611–642.

Hennig-Thurau, T., Gwinner, K., Walsh, G., & Gremler, D. (2004). ELECTRONIC WORD-OF-MOUTH VIA

CONSUMER-OPINION PLATFORMS: WHAT MOTIVATES CONSUMERS TO ARTICULATE THEMSELVES ON THE INTERNET? *Journal of Interactive Marketing*, *18*(1), 38–52.

Howison, J., Wiggins, A., & Crowston, K. (2011). Validity Issues in the Use of Social Network Analysis with Digital Trace Data. *Journal of the Association for Information Systems*, *12*(12), 767–797.

King, R. A., Racherla, P., & Bush, V. D. (2014). What We Know and Don't Know About Online Word-of-Mouth: A Review and Synthesis of the Literature. *Journal of Interactive Marketing*, *28*(3), 167–183. http://doi.org/10.1016/j.intmar.2014.02.001

Libai, B., Bolton, R., Bugel, M. S., de Ruyter, K., Gotz, O., Risselada, H., & Stephen, A. T. (2010). Customer-to-Customer Interactions: Broadening the Scope of Word of Mouth Research. *Journal of Service Research*, *13*(3), 267–282.

Liu, D., Brass, D. J., Lu, Y., & Chen, D. (2015). Friendships in online peer-to-peer lending: pipes, prisms, and relational herding. *MIS Quarterly*, *39*(3), 729–742.

Milgram, S., Bickman, L., & Berkowitz, L. (1969). Note on the drawing power of crowds of different size. *Journal of Personality and Social Psychology*, *13*(2), 79–82.

Parker, G. G., Van Alstyne, M. W., & Choudary, S. P. (2016). *Platform revolution : how networked markets are transforming the economy and how to make them work for you* (First edition). New York: W. W. Norton & Company.

Ryan, R. M., & Deci, E. L. (2017). *Self-Determination Theory: Basic Psychological Needs in Motivation, Development, and Wellness*. New York: The Guildford Press.

Salganik, M. J., & Watts, D. J. (2008). Leading the Herd Astray: An Experimental Study of Self-fulfilling Prophecies in an Artificial Cultural Market. *Social Psychology Quarterly*, *71*(4), 338–355.

Sasaki, T., Becker, D. V., Janssen, M. A., & Neel, R. (2011). Does greater product information actually inform consumer decisions? The relationship between product information quantity and diversity of consumer decisions. *Journal of Economic Psychology*, *32*, 391–398. http://doi.org/10.1016/j.joep.2011.02.010

Shibutani, T. (1955). Reference Groups as Perspectives. *American Journal of Sociology*, *60*(6), 562–569.

Snyder, M. (1987). *Public appearances, private realities: The psychology of self-monitoring*. New York, NY, USA: WH Freeman/Times Books/Henry Holt & Co.

Stanislaw, B. (2015). Why Social Is the New Word-of-Mouth Marketing, and What That Means. Retrieved November 15, 2017, from http://www.marketingprofs.com/opinions/2015/26771/why-social-is-the-new-word-of-mouth-marketing-and-what-that-means

Thies, F., Wessel, M., & Benlian, A. (2016). Effects of Social Interaction Dynamics on Platforms. *Journal of Management Information Systems*, *33*(3), 843–873. http://doi.org/10.1080/07421222.2016.1243967

Tucker, C., & Zhang, J. (2011). How Does Popularity Information Affect Choices? A Field Experiment. *Management Science*, *57*(5), 828–842.

Zhang, D., Zhou, L., Kehoe, J. L., & Kilic, I. Y. (2016). What Online Reviewer Behaviors Really Matter? Effects of Verbal and Nonverbal Behaviors on Detection of Fake Online Reviews. *Journal of Management Information Systems*, *33*(2), 456–481. http://doi.org/10.1080/07421222.2016.1205907

Zhao, J., Binns, R., Kleek, M. Van, & Shadbolt, N. (2016). Privacy languages: Are we there yet to enable user controls? In *Proceedings of the 25th International Conference Companion on World Wide Web* (pp. 799–806). http://doi.org/http://dx.doi.org/10.1145/2872518.2890590

Zhou, W., & Duan, W. (2016). Do Professional Reviews Affect Online User Choices Through User Reviews? An Empirical Study. *Journal of Management Information Systems*, *33*(1), 202–228. http://doi.org/10.1080/07421222.2016.1172460