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Popularity cues in online media: A review of conceptualizations, operationalizations, and general effects

Popularitätshinweise in Online-Medien: Ein systematischer Überblick über Konzeptualisierungen, Operationalisierungen und Effekte

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Abstract: Internet users are constantly confronted with metric information about the popularity of goods, services, and content. These popularity cues (PCs)—which we define as *metric information about users' behavior or their evaluations of entities*—serve as social signals for users who are confronted with them. Due to the high relevance that PCs have for organizations, consumers, and scholars, this article provides a systematic overview of PC research. First, we present a theoretical conceptualization for the effects of PCs. Second, we analyze empirical research that focuses on PCs by providing a review of academic, peer-reviewed studies on the direct effects of PCs in online media (N = 61). Third, we utilize the results of our literature review to address current shortcomings in the literature and to provide insights for future research.

Keywords: Literature review, popularity cues, online media, social media

Zusammenfassung: Internetnutzer_innen werden fortlaufend mit aggregierten Daten über die Beliebtheit von Gütern, Dienstleistungen oder (Medien-)Inhalten konfrontiert. Diese Popularitätshinweise (PH), die wir als *metrische Informationen über das Verhalten von Nutzer_innen oder deren Bewertung von Entitäten* definieren, fungieren als (soziale) Signale, an denen sich Anwender_innen orientieren können. Angesichts der hohen Relevanz von PH für Organisationen, Konsument_innen und nicht zuletzt Forscher_innen bietet dieser Beitrag einen Überblick über die Forschung zu PH. Wir stellen dafür 1) Überlegungen zu einer theoretischen Verankerung von PH an, geben 2) mithilfe einer systematischen Literatursynopse bestehender Studien (N = 61) einen Einblick in aktuelle Forschungsarbeiten und nutzen 3) die Befunde unseres Reviews, um bestehende Probleme in der PH-Forschung zu adressieren und Empfehlungen für künftige Forschungsvorhaben zu formulieren.

Schlüsselwörter: Literatursynopse, Popularitätshinweise, Online-Medien, Soziale Medien

Note: This research was supported by the Munich Center for Internet Research (MCIR) and the German Research Foundation [research group "Political Communication in the Online World," subproject 1, grant number 1381]

1. Introduction

Internet users are ubiquitously provided with metric information about the popularity of online goods, services, and content, such as 900,000 Likes for Mark Zuckerberg's latest Facebook post, an average of 2 out of 5 stars by 75 users for a restaurant on Yelp, or a 9.1 film rating by 23,000 movie fans on IMDB. Users can also provide metric ratings and thus contribute to the bulk of available user experiences with products and services. These popularity cues (PCs) directly serve as social signals for users who are confronted with them (Ksiazek, Peer, & Lessard, 2016). Moreover, such PCs are put to algorithmic use within filtered online environments such as social network sites; thus, they can also serve as indirect signals for users through the selection and arrangement of information based on its popularity (Napoli, 2010). As prior research shows, PCs are both directly and indirectly able to influence users' perceptions of the entity associated with PCs. Hence, they might affect the users' subsequent decisions in terms of selection, usage, and evaluations.

In research, however, PCs suffer from strong conceptual and operational ambiguity. As such, they are operationalized as both independent and dependent variables. While, strictly speaking, the term 'cue' is misleading due to its connotation of decisiveness, which suggests an effect on users, a plethora of terms are used to denote PCs as independent variables. The variety of terms ranges from "bandwagon cues" (Kim & Sundar, 2014) and "helpfulness ratings" (Walther, Liang, Ganster, Wohn, & Emington, 2012) to "social media metrics" (Stavrositu & Kim, 2014) and "social endorsement cues" (Messing & Westwood, 2014, p. 1046). Theoretical conceptualizations of PCs also vary, including arguments related to word-of-mouth (Duan, Gu, & Whinston, 2008), involvement (Kim, Brubaker, & Seo, 2015), exemplification (Peter, Rossmann, & Keyling, 2014), and news-value (Weber, 2014) theory. Moreover, PCs are presented in either real-world (e.g., Facebook) or fictitious environments, are visualized either graphically (e.g., star ratings) or numerically, refer to actual (e.g., Likes for a post) or follow-up (e.g., Likes for a comment) content, describe content (e.g., Likes for a post), usage (e.g., number of clicks), diffusion (e.g., number of shares), or follow-up communication (e.g., number of comments), and possess either an evaluative character (e.g., Likes) or are non-evaluative per se (e.g., clicks). However, a systematic overview of the conceptualizations, operationalizations, and general effects of PCs is still missing.

A systematic overview of PCs is crucial for a coherent understanding of how the perception of others' behaviors and evaluations could affect individual users under various circumstances. Many studies refer to PCs as a central feature of social network sites, news aggregation, and e-commerce. Yet, this strong dependence on context results in the fragmentation of conceptual assumptions, thus hampering a comprehensive perspective. In those studies, the equivocal variety of conceptualizations and operationalizations allows for cherry-picking of suitable findings. It does not facilitate a systematic overview of the possible effects of PCs. For example, while some empirical findings have shown that PCs affect users' news selection (e.g., Yang, 2016), other studies suggest that PCs only have a very limited effect (e.g., Knobloch-Westerwick, Sharma, Hansen, & Alter, 2005).

Moreover, various moderating influences have been identified, but these have only been discussed from the perspective of highly specific scenarios.

Thus, this paper aims to provide a generalizable overview of the effects of PCs in online media that were studied up to this point. To do so, we first embed the concept of PCs within the broader contexts of relevance cues and attentional processes. Building upon this theoretical foundation, we provide a review of academic, peer-reviewed studies to systematically collect and analyze empirical findings on the direct effects of PCs in online media (N = 61). Coding included all aspects of the empirical studies that are both comparable and relevant from a media effects perspective. This included the main field of interest, the methodology, operationalization, dependent and moderating variables, and outcome. However, due to the wildly varying methodological approaches used in the reviewed studies, we could not apply common meta-analytic procedures. Rather, we provide a quantitative descriptive overview of the investigated studies. Ultimately, we utilize the results of our review to address current shortcomings in the literature and to provide insights for future research.

1.1 Popularity cues in online media

Despite the variety of terms and theoretical conceptualizations, scholars agree on various principles with regard to PCs. First, PCs represent meta-information about the popularity of an entity (e.g., a product, social-media post, or news article). By itself, meta-information is neither inherent to nor entirely dependent on an entity's manifest characteristics. From a general perspective, the informational value of PCs merely can be seen as a cue for further interpretation (for a literature overview on PCs as *results* of prior behavior, see Porten-Cheé et al.'s paper in this issue). For example, a news article might get several thousand Likes on Facebook, whereas the exact same article might only receive a few Hearts on Twitter. Second, PCs reveal either intended user-generated information (e.g., ratings) or unintended (observed) user-generated information (e.g., number of clicks). Yet, in reality, PCs do not necessarily rely on or reveal this discrimination. Thus, their value could be user-generated, observed, or a (nontransparent) combination of the two. Third, PCs depict metrics rather than qualitative data (e.g., comments). That said, PCs are not necessarily presented as plain numbers. Instead, they might also be illustrated, for instance as an icon or as a graphic image.

In line with these concurring principles, we define PCs as *metric information about users' behavior or their evaluations of entities*. However, the term *popularity* requires further clarification. First, popularity implies an indication of relevance, be it positive or negative, among a population. Second, it refers to a population among which the perceived popularity is valid. This population can be known or unspecific. Moreover, it could either be platform-driven (e.g., popular on Twitter) or externally constructed (e.g., popular among U.S. citizens), both of which are subject to individual interpretations. That being said, PCs do not *per se* indicate the same kind and amount of relevance to every user. Thus, the meaning of PCs—whether they are 'high' or 'low' or whether they indicate favorable or unfavorable evaluations—can only be ascribed by users and their individual assessments. This process includes (unconsciously) weighting PCs against each other, incorporating prior knowledge, or considering one's presumptions about the evaluated entity. Therefore, PCs can be understood and categorized under the umbrella concept of *relevance cues*, which, depending on the users' individual assessments of the PCs under consideration, may or may not affect their evaluations of a given entity. However, the concept of relevance cues is neither necessarily limited to online or metric information nor does it solely serve as an indication of popularity.

1.2 Popularity cues as relevance cues

Relevance cues are indicators that signal a certain level of importance to media recipients. They offer information regardless of the actual elaboration of the content. Relatedly, *peripheral cues* refer to indicators that trigger heuristic content elaboration, but these cues do not necessarily depict relevance (Petty & Cacioppo, 1986). Apart from that, to the best of our knowledge, no systematic differentiation of relevance cues exists. Thus, we distinguish between four types of relevance cues. First, *internal relevance cues designated by the originator of a message* include all kinds of signals that are intentionally included in an entity (e.g., in a news article or a product description) to indicate importance, such as highlighted news values (e.g., "the biggest environmental disaster in human history"), celebrity endorsements (e.g., "Rihanna supports this campaign"), or linguistic features (e.g., exclamation marks). Second, *external relevance cues designated by the originator of a message* include signals that are intentionally attached to an entity and indicate importance relative to other entities. Such cues include labels (e.g., "editor's pick"), layouts, or an item's ranking on a website. Third, *external relevance cues designated by intermediaries* depict intentionally attached signals to an entity by a third party that is neither the originator nor user of a message (Helmond, 2015; Nielsen & Ganter, 2017). Examples include algorithmically derived rankings or personalization features which present information because they supposedly fit users' preferences. Fourth, *external relevance cues designated by users* are signals attached to an entity that are intentionally or unintentionally produced and curated by recipients or consumers. In contrast to relevance cues designated by either the originator of a message or intermediaries, relevance cues designated by users indicate a level of popularity among those users. In the context of TV talk shows, Nabi and Hendriks (2003) referred to these types of cues as audience-response cues. While these might include live reactions on TV or radio, such as applause, individual close-up reactions, or telephone polls, our more general understanding also includes online reactions, such as comments or metric information about users' behavior or their evaluations of entities—that is, PCs.

The possible effects of these types of relevance cues may differ. While internal and external relevance cues designated by the originator of a message as well as external relevance cues designated by intermediaries (i.e., types one, two, and three) suggest that users follow the originator's guidance, external relevance cues designated by users indicate broader opinions that, in turn, might be perceived as more independent and diverse. Because it is generally assumed that people surveil their environment in order to perceive public opinion, people build their perceptions on cues that indicate relevance (Hardmeier, 2008; Noelle-Neumann, 1974). External relevance cues designated by users thus have the potential to affect perceptions of public opinion (see Porten-Cheé et al.'s related discussion in this issue). Despite the potential effectiveness of relevance cues, individuals' perceptions of relevance cues are neither static nor immutable. Rather, they evolve over time, depending on individual usage patterns, technological capabilities, and societal assumptions. For example, most likely, the number of Likes will be associated with 'positive popularity' (acclaim, approval), whereas the number of 'angry emoticons' may be associated with 'negative popularity' (blame, disapproval). In the remainder of this paper, we focus on the current conceptualizations of PCs as external relevance cues designated by users.

1.3 Popularity cues and attentional processes

To the best of our knowledge, no dedicated theoretical conceptualizations of the attentional processes associated with PCs exist within communication studies. Yet, the field of social cognition offers insights into people's information processing, which may help explain how PCs could affect a) attentional processes and, subsequently, b) the formation of users' impressions.

Inherently, the perception of information begins with *attention* toward said information (Bodenhausen & Hugenberg, 2009). Due to limitations of cognitive capacity, attention can only be ascribed selectively (Posner, 1994). Which information receives (selective) attention is subject to a process that involves a broad variety of influences, and it starts with "preattentive scans of the environment" (Bodenhausen & Hugenberg, 2009, p. 4). According to Bodenhausen and Hugenberg (2009), information either grabs a person's attention (bottom-up) or a person actively seeks certain information (top-down). Once an entity is within a person's subconscious attention, various (contradicting) evaluation mechanisms come into play. In terms of media content and the formation of people's impressions, three concepts address such evaluation mechanisms: vividness, salience, and differential attention.

First, *vividness* has served as a discriminating cue in which content is perceived as either lively and worth remembering or dull and apt to be ignored (Kisielius & Sternthal, 1984, 1986; Taylor & Thompson, 1982). In this regard, popularity is directly attached to an entity. Thus, it represents an absolute measure because it allows an entity to be rated as vivid without comparing it to another entity. We call this a between-subjects indication of popularity (i.e., a bottom-up signal for attention). In order for PCs to act in this way, a consensus would be necessary in which the recipients, the originators, and the researchers agree on 'high' and 'low' levels of PCs. Yet, while this sometimes is possible (e.g., five stars are generally more captivating than three stars), oftentimes, and especially with raw numbers, this is not the case because PCs depend on the perceived characteristics of an entity. For instance, while 230 product reviews might be 'a lot' when considering buying a new belt, it may as well be 'not much' when it comes to a new smartphone. Thus, vividness is an approach that cannot solely explain the attentional processes prompted by PCs.

Second, the concept of *salience* describes the relevance people ascribe to issues[1]. Among other factors, salience subsequently leads people to derive rank-orders; thus, it is attached to an individual person rather than the issue itself (Evatt, 1997; Kiousis, 2004). We refer to this as a within-subject indication of popularity (i.e., a top-down attribution of attention). For example, while one person might consider 6 out of 10 points to be a high rating, someone else might find a minimum value of 8 points to be acceptable. Moreover, salience is likely to vary systematically within subjects, depending on the PCs under consideration. A person might rely on the rating for movies (e.g., 6 out of 10 points), whereas the same individual might primarily focus on the *amount* of ratings for printer supplies (e.g., 230 ratings). While salience seems widely applicable to the concept of PC-driven attentional processes, it ignores the influence of content-specific characteristics.

Third, for the analysis of attentional processes to media stimuli, Brosius and Mundorf (1990; original publication in German) describe a concept they call *differential attention*[2]. They suggested looking at both vividness and salience simultaneously when analyzing attentional processes to media stimuli, because in real life neither of the concepts occurs in isolation. However, in the past, researchers have primarily examined vividness and salience in separate studies, which increases the risk of confounding. For example, in experimental vividness studies, two groups of participants are often presented with vividly diverging stimuli, but the differences in the studies' outcomes may also be due to variations in individual salience. Following ideas from the field of social cognition (Nisbett & Ross, 1980), Brosius and Mundorf (1990) noted that it is important to understand the use of media content as an integrated combination of content-specific aspects (i.e., between-subjects vividness) and cognitive aspects (i.e., within-subject salience). Moreover, Brosius and Mundorf (1990) suggested including culture-bound aspects, which were already proposed as influential aspects within the news-value theory (Galtung & Ruge, 1965). For instance, to a movie enthusiast (salience) from Mumbai, a Facebook post with 2.2 million Likes (vividness) by an Indian film actor, such as Aamir Khan (culture-boundedness), might have a higher relevance than a similar post by a U.S. film actor, such as Tom Cruise.

Taken together, for PCs to attract attention and, subsequently, have an influence on users' perceptions, *context* is necessary. Such context allows plain numbers to be put into perspective, and it allows users to compare PCs with each other. These comparisons can be achieved in different ways. First, comparisons can be *synchronic* or *diachronic*. While in synchronic situations multiple PCs are available for direct comparison (e.g., two product reviews presented next to each other), diachronic comparisons are made when PCs are shown in distinct situations that occur over time (e.g., when clicking through various products). Hence, synchronic comparisons are factual comparisons, whereas diachronic comparisons rely on the users' memory. Second, comparisons can also be *explicit* or *implicit*. That is, while

1 Originally, the concept of salience was only applicable to issues. For the PC context, however, salience can be ascribed to issues as well as to posts, products, or, broadly speaking, entities.

2 The authors thereby applied the already known psychological concept (e.g., Taylor & Thompson, 1982) to media-effects research.

a comparison may rely on the actual PCs of two entities, it can also rely on general assumptions based on earlier encounters with similar entities. For example, when being confronted with a *New York Times* news article and its 723 Facebook Likes, a user might compare this with either another article containing 512 Likes (explicit comparison) or with his/her perception of *New York Times* articles generally receiving several hundred Likes (implicit comparison).

Currently available research has not adequately dealt with these contextual characteristics. By subsuming PCs under the umbrella concept of relevance cues, and by considering the fact that the perception of these relevance cues evolves over time, we also suggest that users are capable of *learning* the significance of such cues. This assumption is in line with social-learning theory as well as the literature on perceived self-efficacy (Bandura, 1977). For example, when browsing Facebook every day a user might get a feeling about the value of Likes, and, thus, be able to differentiate between posts from different originators and their levels of Likes. Likewise, a tourist that always visits booking.com when planning a trip eventually 'knows' how many ratings provide a reliable forecast for a good vacation. Thus, variations in both attentional processes and possible effects over time are expected.

2. Literature review

In light of the theoretical conceptualizations offered above, we now turn to empirical findings in the domain of PCs by providing a review of academic, peer-reviewed studies that examine different general effects of PCs in online media.

2.1 Literature search procedure

All the papers discussed in this literature review were obtained by searching the following databases: Communication & Mass Media Complete, Web of Science, Association for Computing Machinery (ACM) Digital Library, and Google Scholar. With one exception, all of the search results were screened; for Google Scholar results, only five result pages were taken into account as this database also presents related hits rather than direct hits, thus increasing the number of results to an unmanageable amount. The papers had to empirically focus on the effects of *metric* user information (e.g., "256 users recommend this book") to be part of our sample. Papers that did not focus on metric-related effects of user information (e.g., effects of evaluative comments, such as "This book is awesome!") were explicitly excluded. To address the problem of conceptual diversity, we defined two groups of search terms (see Table 1). All reasonable combinations of the terms within the first (n = 5) and second (n = 8) group, such as 'popularity cues', were used to search for potential papers to include in the review. Additionally, the terms 'approval ratings' and 'rating visualizations' were included since several of the papers listed them as additional keywords. During the database search process, all the terms were used in quotation marks to enable searching for exact phrases.

Table 1. Search terms used in the literature search procedure

Search Term Group 1	Search Term Group 2
popularity	indicators
bandwagon	indications
social media	bandwagons
user	cues
interface	information
	metrics
	ratings
	recommendations

Moreover, papers had to have been published between 2005 and 2015. Two reasons justified this chosen time period. First, 2005 was chosen as a starting point since social-media platforms and so-called Web 2.0 applications started to gain popularity at this time, thereby also encouraging scientific investigations. These platforms and applications changed and accelerated the development of recommendation systems, further facilitating the ubiquity of PCs that is prevalent today. Second, 2015 was chosen as the end-point because we wanted to include research trends in *recent* academic discourses on PCs. This was also the reason why we not only focused on papers in academic journals but also included peer-reviewed conference manuscripts (full papers only) that tend to be published faster. Presumably, this enabled us to include papers that reflect ongoing research more appropriately.

The initial search yielded 133 unique papers that appeared to be meeting the access criteria based on the title and abstract. At least to some degree, relevant papers (peer-reviewed conference manuscripts or journal articles) had to empirically deal with PCs—defined as metric information about users' behavior or their evaluations of entities. Ultimately, 55 articles met our inclusion criteria after thorough reading (see Table 2). Six articles contained two studies, leading to 61 studies that were quantitatively coded. Due to the large variety of methodological approaches, and, in some instances, insufficient statistical disclosure, we were unable to conduct a statistical meta-analysis of the effect sizes.

Table 2. List of analyzed publications, sorted by name of the author(s)

Author(s)	**Year of Publication**	**Context**	**Method**
Ali, Parsons, & Ballantine	2013	E-Commerce and Marketing	Interview, experimental
Arora, Arora, & Palvia	2014	E-Commerce and Marketing	Content analysis, non-experimental
Bronstein	2013	Online Communities	Content analysis, non-experimental
Buder, Schwind, Rudat, & Bodemer	2015	Online News	Interview, experimental

Author(s)	Year of Publication	Context	Method
Chintagunta, Gopinath, & Venkataraman	2010	E-Commerce and Marketing	Content analysis, non-experimental
Duan, Gu, & Whinston	2008	E-Commerce and Marketing	Content analysis, non-experimental
Flanagin, Metzger, Pure, Markov, & Hartsell	2014	E-Commerce and Marketing	Interview, experimental
Fu	2012	Online Communities	Content analysis, non-experimental
Go, Jung, & Wu	2014	Online News	Interview, experimental
Ha, White, & Wyer	2012	E-Commerce and Marketing	Interview, experimental
Hu & Pu	2014	E-Commerce and Marketing	Interview, non-experimental
Jin, Phua, & Lee (2)	2015	Online Communities	Interview, experimental
Kelly, Cushing, Dostert, Niu, & Gyllstrom	2010	Search Engines	(Online-)Observation, experimental
Kim	2014	Online Communities	Interview, non-experimental
Kim, Brubaker, & Seo	2015	E-Commerce and Marketing	Interview, experimental
Kim & Sundar	2014	Online Communities	Interview, experimental
Kim & Sundar	2011a	E-Commerce and Marketing	Interview, experimental
Kim & Sundar	2011b	Online Communities	Interview, experimental
Knobloch-Westerwick, Sharma, Hansen, & Alter	2005	Online News	(Online-)Observation, experimental
Ksiazek, Peer, & Lessard	2014	Online News	Content analysis, non-experimental
Lau, Kwok, & Coiera	2011	Search Engines	Interview, experimental
Lee	2009	E-Commerce and Marketing	Interview, experimental
Lee & Jang	2010	Online News	Interview, experimental
Lee & Tan	2013	E-Commerce and Marketing	Content analysis, non-experimental
Leino, Räihä, & Finnberg	2011	Online News	Interview, non-experimental
Lim & Steffel	2015	E-Commerce and Marketing	Interview, experimental
Luo, Andrews, Song, & Aspara	2014	E-Commerce and Marketing	(Online-)Observation, non-experimental

Author(s)	Year of Publication	Context	Method
Messing & Westwood (2)	2014	Online News	Interview, experimental
Neo	2010	E-Commerce and Marketing	Interview, experimental
Nov & Arazy	2015	E-Commerce and Marketing	Interview, experimental
Peter, Rossmann, & Keyling	2014	Online Communities	Interview, experimental
Porten-Cheé & Eilders	2015	Online News	Interview, experimental
Ringelhan, Wollersheim, & Welpe (2)	2015	Online Communities	Content analysis, non-experimental
Rudat & Buder (2)	2015	Online Communities	Interview, experimental
Salganik, Dodds, & Watts (2)	2006	Online Communities	Interview, experimental
Scott	2014	Online Communities	Interview, experimental
Sparling & Sen	2011	E-Commerce and Marketing	Interview, experimental
Stavrositu & Kim	2014	Online Communities	Interview, experimental
Sugimoto, Thelwall, Larivière, Tsou, Mongeon, & Macaluso	2013	Online Communities	Content analysis, non-experimental
Sundar, Oeldorf-Hirsch, & Xu	2008	E-Commerce and Marketing	Interview, experimental
Sundar, Xu, & Oeldorf-Hirsch	2009	E-Commerce and Marketing	Interview, experimental
Thuy, Vi, & Linh	2015	E-Commerce and Marketing	Interview, experimental
Totti, Costa, Avila, Valle, Meira, & Almeida	2014	Online Communities	Content analysis, non-experimental
Tsay, Dabbish, & Herbsleb	2014	Online Communities	Content analysis, non-experimental
Tucker & Zhang	2011	E-Commerce and Marketing	(Online-)Observation, experimental
Walther, Liang, Ganster, Wohn, & Emington	2012	E-Commerce and Marketing	Interview, experimental
Weber	2014	Online News	Content analysis, non-experimental
Winter & Krämer (2)	2014	Online News	Interview, experimental
Winter, Krämer, Appel, & Schielke	2011	Blogs	Interview, experimental
Winter, Krämer, Appel, & Schielke	2010	Blogs	Interview, experimental

Author(s)	Year of Publication	Context	Method
Xenos, Macafee, & Pole	2015	Online Communities	Content analysis, non-experimental
Xu	2014	E-Commerce and Marketing	Interview, experimental
Xu	2013	Online News	Interview, experimental
Xu, Hao, & Younbo	2015	E-Commerce and Marketing	Interview, experimental
Yang	2015	Online News	(Online-)Observation, experimental

Note: Articles containing more than one study are followed by the number of studies in brackets (e.g., "(2)" for two studies). The complete list—containing title and outlet of the publication—can be requested from the authors.

2.2 Literature categorization

The categories of the quantitative analysis were derived from literature reviews in the domain of social media (Kümpel, Karnowski, & Keyling, 2015; Zhang & Leung, 2015). Due to the given similarity of this research area (online context, similar 'key players,' anonymous yet public communication sphere) the cited reviews served as a valuable starting point. The derived categories included (a) *year of publication* and *article type* (conference manuscript, journal article), (b) *methodological approach* (interview, content analysis, observation; each experimental or non-experimental), and (c) *study context* (online news, blogs, e-commerce, search engines, online communities, and marketing). We coded the study context by assessing the way in which the papers were framed. If a study, such as one by Messing and Westwood (2014), showed that source cues affect the selection of online news stories, we coded it within the context of 'online news.' Studies, such as one conducted by Neo (2010), which found that helpfulness ratings had no effect on purchase intentions, were coded as 'e-commerce.'

Afterward, we extended the list of categories in order to encompass all aspects relevant to the investigation of PCs. This extension was based both on the theoretical discussion of attentional processes as well as on a qualitative inspection of the studies, which allowed us to obtain an impression of the research field. In line with our focus on media effects, we thus included (d) *type of PC* (clicks, Likes, comments, shares, Tweets, favorites, Retweets, rating scales, others), (e) *operationalization of PC extent* (e.g., two-digit number for 'low popularity'), (f) *(in)dependent and moderator variables*, and (g) the *existence of effects* (no effect, nuanced effect, positive effect).

We categorized PC operationalization by focusing on three dimensions. First, we distinguished between PCs that are actually deployed (e.g., Facebook Likes, Amazon stars) and PCs that cannot be found in recent online environments (e.g., Facebook dislikes, friendship popularity). Second, we coded the exact types of PCs (e.g., clicks, Likes, rating scales), allowing for multiple codings if a study focused on more than one type of PC. Third, for all studies that experimentally varied PCs (*n* = 11), we also coded the operationalization of the PC extent, indicating what researchers define as 'low' and 'high' PC extents. Furthermore, for all studies that investigated PCs as the independent variable (*n* = 47), we coded the reported effects as: (a) none, (b) nuanced, or (c) mostly positive. Moreover, we coded both the dependent and moderating variables as open-ended variables in a first step and re-coded them into categories in a second step. Due to the large variability and, in some instances, the sheer absence of theoretical grounding, no category was established to code the studies' underlying theoretical assumptions.

All studies were read and coded by the authors of this paper in discursive sessions, following three steps. First, all authors of this and Porten-Cheé et al.'s manuscript (in this issue) read and coded the studies with a code sheet that included the categories described above, but, in a first step, only asked for open-ended codings. Second, these initial results were discussed and adjusted during a one-day workshop in early January of 2016. Third, codings were refined and, if possible, quantified in another round of discursive sessions with all authors of this manuscript. This procedure called for profound arguments for all codings but prohibited the calculation of inter-coder reliability.

3. Results

Our sample of articles (*N* = 55) includes 42 journal articles and 13 conference manuscripts.[3] While only two articles were published prior to 2008, no conference manuscript from that time met our access criteria (see Table 3). This distribution supports our methodological justification for the chosen starting point of the investigation. Furthermore, the high number of journal articles published in 2014 (*n* = 15) and 2015 (*n* = 10) highlight the current empirical relevance of the topic in the field.

Focusing on all studies rather than articles (*N* = 61), interviews were conducted in a majority of the studies (*n* = 42). Most of these interviews incorporated experimental variations (39). Out of five (online) observations, four also followed a post-hoc experimental approach. The remaining 14 studies were content analyses. Overall, PCs were investigated as both dependent and independent variables, thus allowing for conclusions about the *effects* derived from PCs and the factors *influencing* PCs. However, the majority of the studies investigated PCs (also) as the independent variable (*n* = 52).

3 The two subsamples of journal articles and conference manuscripts do not overlap, except for two cases: Kim and Sundar (2011) and Winter and Krämer (2014).

Table 3. Number of articles investigating PC between 2005 and 2015

			Year of Publication											
			2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total
Article type	Conference Manuscript	count	-	-	-	1	1	3	3	-	1	2	2	13
		in %	-	-	-	8	8	23	23	-	8	15	15	100
	Journal Article	count	1	1	-	1	1	2	4	3	4	15	10	42
		in %	2	2	-	2	2	5	10	7	10	36	24	100
Total		count	1	1	-	2	2	5	7	3	5	17	12	55
		in %	2	2	-	4	4	9	13	6	9	31	22	102

Note: Discrepancies from 100% in total are due to rounding.

3.1 Contexts in which popularity cues were investigated

The results seem to reflect the utilization of PCs within actual online environments. As such, *e-commerce and marketing* (n = 23; e.g., shopping websites) and *online communities* (n = 20; e.g., social network sites) dominate our sample of studies (N = 61). Despite this bias, *online news* (n = 14) clearly prime the rest of the sample before *blogs* (2) and *search engines* (2).

3.2 How popularity cues are operationalized

PCs are operationalized in a wide variety of ways. First, PCs that are actually deployed (rather than PCs that cannot be found in recent online environments) allow recipients to draw upon the knowledge they gained from prior usage. For example, if a study is set in a Facebook setting, users of the site are likely to know what Likes or Shares indicate. While in most studies the second type of PCs is modeled after actual PCs, users cannot build upon prior knowledge when trying to make sense of the numbers that are depicted. For example, Hu and Pu (2014) employed both Likes and Dislikes in an experimental interview where participants were able to draw upon their prior knowledge about Likes, but they could not build on their experiences with Dislikes. Out of N = 61 studies, 28 used actual, existing PCs, whereas 33 used PCs that cannot be found in current online environments. While studies in the context of online news were equally distributed, the majority of studies within e-commerce and marketing used non-existent PCs (n = 17). The opposite is true for online communities, where 15 out of 20 studies built on actual, existing PCs, mostly taken directly from the online community under investigation.

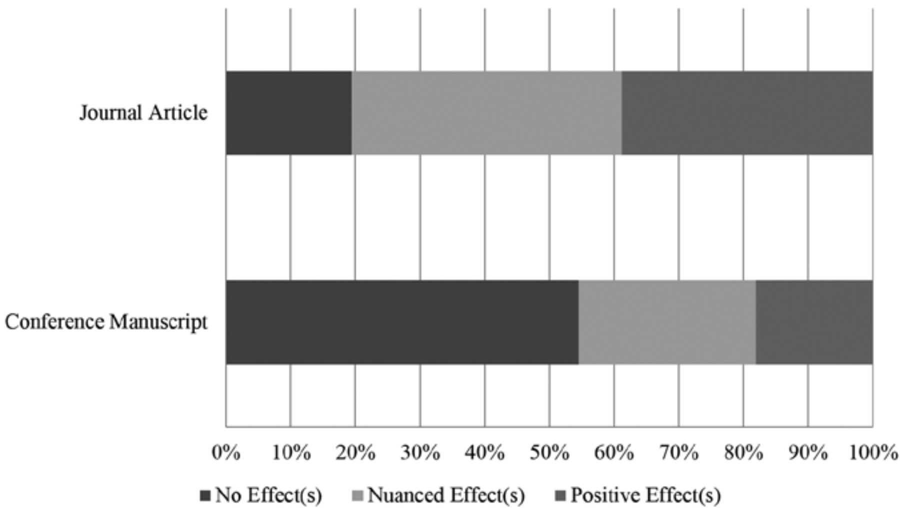
Second, we found a strong tendency toward *rating scales* within the studies building on fictitious PCs—out of 33 studies with fictitious PCs, 25 used rating scales (solely or among other PC types). For example, Lee (2009) investigated the effects of favorability on a made-up, seven-point rating scale. Real PCs in the studies mostly incorporated *clicks* (in 9 studies), *Facebook Likes* (6), *comments* (5), and *rating scales* which are currently deployed and in use (7), such as five-star rating scales (e.g., Knobloch-Westerwick et al., 2005).

Third, for all the studies that experimentally varied the PCs (N = 11), a clear pattern emerged in which one-digit numbers (n = 7) or two-digit numbers (n = 4) were used as a low PC extent (e.g., 7 Likes, 42 clicks). For the manipulation that included high PC extents, eight studies used three-digit numbers and three studies utilized four-digit numbers (e.g., 256 clicks, 1,024 comments). While three studies reported pre-tests and two studies referred to similar research in order to disclose how these numbers were derived, six studies experimentally varying PCs did not justify their operationalization.

3.3 What effects popularity cues imply

The results suggest a Facebook relationship status as a conclusion—"it's complicated": While 16 studies found mostly positive effects, 18 reported nuanced effects, and 13 did not find any effects. This distribution varies strongly when conference manuscripts and journal articles are examined separately. This indicates a publication bias toward studies finding (at least nuanced) effects (see Figure 1). Due to the already limited number of studies that consider moderator variables, and due to the fact that the moderators are usually closely related to the specific object of investigation, we were unable to deduce quantitative tendencies. Yet, we offer exemplary insights whenever possible. Overall, our review shows that the effectiveness of PCs cannot be determined in advance.

Figure 1. Existence of effects by article type



The strongest PC effects were derived from studies within the context of e-commerce and marketing (see Table 4). In that context, the affected dependent variables included further behavior (e.g., intention to purchase), selection (e.g., clicking on a specific product), and rating (e.g., submitting a star rating after being exposed to PCs). Nuanced effects included PC effects under specific circumstances. In that regard, the moderator variables include sociodemographic information, the characteristics of the entity itself (e.g., the weight or look of a product), and the participant's involvement. For example, in the context of movie selection decisions, Xu et al. (2015) found that participants who were less familiar with Hollywood movies relied more on PCs when they made viewing decisions than participants with higher movie familiarity.

Table 4. Existence of effects by research context

	Effect(s)			
Research Context	No effect(s)	Nuanced effect(s)	Positive effect(s)	Total
Online News	3	3	6	12
Blogs	2	0	0	2
E-Commerce and Marketing	3	4	10	17
Search Engines	2	0	0	2
Online Communities	3	9	2	14
Total	13	16	18	47

Within online news, half of the studies reported positive PC effects. Those studies included dependent variables, such as selection (e.g., clicking), evaluation (e.g., ascribing higher quality), and further behavior (e.g., intention to comment or share). Nuanced effects within the context of online news are due to the topic and involvement, need for cognition, and prior knowledge. Such nuanced effects call for a more differentiated view of PC effects in the context of online news—a recommendation addressed by Porten-Cheé et al.'s paper in this issue.

In online communities, most of the PC effects are nuanced, including all kinds of moderator variables, such as a post's characteristics (e.g., image, headline, sharing originator), a recipient's involvement, third-person perception, and need for cognition. Studying the effects of PCs—referred to as indirect social information—Peter and colleagues (2014) investigated the moderating role of the participants' perceived importance of PCs. They expected participants that attached greater importance to PCs to be influenced more strongly by PCs than participants that assigned only little importance to them. However, they observed no such effect.

4. Moving forward in studying popularity cues: Concluding remarks

Scholars from a wide variety of academic disciplines and fields, such as communication, marketing, social psychology, and economics, have recognized the increasing importance of PCs in online media. PCs provide users with metric information about popularity; thus, they help them to make decisions in various situations, such as when they select or evaluate goods, services, or content. However, in empirical research, PC researchers have been—and still are—confronted with strong conceptual and operational ambiguities. By locating PCs under the umbrella concept of relevance cues, providing a widely applicable definition, and discussing the attentional processes that lay the foundation for further effects, we first tried to decrease this ambiguity and establish a theoretical basis for studying

PCs. Second, we analyzed existing empirical research on PCs by conducting a comprehensive literature review of academic, peer-reviewed studies published from 2005 to 2015, thus uncovering research patterns and trends in scholarly activities. Building on this analysis, our literature review suggests that a prototypical study on PCs uses *experimental surveys* to examine the effects of *rating scales* on users' *evaluations* in an *e-commerce* setting. It uncovers *nuanced effects* prone to moderating influences, such as a participant's *involvement* and an entity's *characteristics*. In the context of our theoretical conceptualization, external relevance designated by others is apt to affect a user's evaluation of an entity under certain circumstances. We categorize these moderating circumstances as top-down vividness and bottom-up salience. For example, PCs may affect users more when a given product appears to be specific and useful (vividness; e.g., Tucker & Zhang, 2011). At the same time, PCs have the potential to have a greater effect on users within e-commerce settings if users are more involved with the purchase task (salience; e.g., Sundar, Xu, & Oeldorf-Hirsch, 2009).

We acknowledge that a scientific literature review such as ours is naturally limited by decisions made early in the research process. By choosing to only include articles that could be found with a predefined set of keywords, it is possible that we omitted research that would also have been relevant for the review. While we tried to account for publication bias by also including conference manuscripts, we ignored other sources, such as unpublished papers, dissertations, or research presented in edited volumes or monographs. Moreover, as this study mostly relied on a vote-counting approach (Bushman & Wang, 2009), the quality of the studies, the size of the samples, or the size of the identified effects were not systematically taken into account. Despite these limitations, we believe that our review provides useful guidance for researchers. In this concluding section, we seek to take the results of both the general discussion and the literature review one step further by providing concluding remarks on current PC research. By doing so, we offer suggestions on how scholars can move forward in conducting PC research.

Conclusion I: *The meaning of PCs has to be learned. The more experience users have with PCs, the better they are able to use them in their selection and navigation behavior.*

Context and implicit or explicit reference points are necessary for PCs to be effective. This seems especially relevant when conducting experimental research on the effects of PCs. If researchers do not provide participants with hints on how given PCs can be interpreted (e.g., by providing explicit points of comparison or by disclosing which metric values indicate 'high' or 'low' popularity), participants are forced to interpret PCs on their own. As most of the experimental studies did not justify their PC operationalizations, this poses a threat to experimental external validity, and it hampers causal inferences. Moreover, it might be interesting to investigate whether Internet users have already established a sense for interpreting PCs' extents—regardless of the reference points. It might be helpful for researchers to expose a large number of participants to different types and amounts of PCs, and ask them about their perceptions. This might uncover the learning effects induced by repetitive exposure to PCs. Notwithstanding the above, it seems generally necessary to carefully consider the contextual information that participants use as a basis for their evaluations of PCs—be it in experimental settings or when examining PCs theoretically.

Conclusion II: *The effectiveness of PCs depends on external factors, such as user variables (e.g., informational needs, behavioral intentions, and involvement) as well as the context variables that determine the vividness and/or salience of PCs.*

While the availability of implicit or explicit reference points is necessary for PCs to be effective, context alone is not sufficient. Instead, the effectiveness of PCs depends on the general traits or situational interests and characteristics of the user. For example, in an online shopping situation, PCs might be irrelevant after the purchase decision has been made. However, if the user is (virtually) window-shopping and still in a stage of information seeking, PCs have the potential to influence purchase intentions. Likewise, the users' level of involvement—reflecting how personally important or interested a user is in buying a product or consuming specific content—moderates PCs' effectiveness. Decisions that are routine, as well as decisions that have been made before, are probably far less influenced by PCs than decisions a user is unfamiliar or uncertain with.

However, no entity (whether a product or a type of media content) is involving *per se*. While buying office supplies might be a routine and low-involvement situation for one individual, another individual—who has had a poor experience with previous purchases or who is concerned about environmental issues—might be highly involved in the same situation. Thus, controlling the influence of involvement seems to be a substantial factor in PC research. Relevant factors that could influence an individual's level of involvement include the availability of alternatives (2 v. 200 available products), the necessity of the decision (mandatory purchase decision of a new refrigerator v. optional viewing of information, such as a product description or a news article), and its reversibility.

Our literature review showed that moderating influences, such as the users' involvement, their need for cognition, or their prior knowledge, are already included in some empirical studies on PCs. However, experiments often force decisions on participants. That is, they make participants choose between alternatives when, in real-life, a decision would not be mandatory (e.g., "Which of these news articles would you most likely want to read?"). Thus, a more differentiated view on actual PC usage situations would strengthen the external validity of PC studies.

Conclusion III: *To move forward in PC research, it is necessary to develop a comprehensive theoretical framework that is open to emerging and evolving online environments.*

While we already tried to address the conceptual ambiguity in the field of PCs by offering a definition under the umbrella concept of relevance cues, it seems inevitable to develop a comprehensive theoretical framework. Such a framework should take attentional processes, (media) effects, and user motivations into account (e.g., why do people rate movies on IMDB, give Likes for Facebook posts, or rate products they bought on Amazon?). Put into a scholarly context, a more recipient-centered approach along the lines of uses-and-gratifications research seems promising and beneficial. Moreover, existing models/theories of persuasion and information processing, such as the Elaboration-Likelihood Model or informational utility approaches, could be used to conceptualize the effects of PCs (see Porten-Cheé et al.'s paper in this issue).

Ultimately, PC research needs to keep up with recent and rapidly changing developments in online communication. For example, since Facebook launched its 'Facebook Reactions' in February 2016, the variety of PCs—at least in social media—has increased considerably. Users are still able to 'Like' content on Facebook, but they can also express whether it made them laugh, sad, or angry, and whether they loved it or were astonished by it. Thus, not only are users able to easily show reactions that go beyond approval, they can also obtain a better sense of what others think about a post, a specific type of content, or even a societal issue. In this regard, PCs might potentially disrupt traditional scholarly perspectives, such as news-value theory. Importantly, PCs might depict relevance toward recipients as well as communicators (e.g., journalists, e-marketers). Studies have already shown that, for instance, online newsroom editors "are relying more and more on digital tracking tools to understand the popularity of news items in order to maximize their presentation of content that audiences will be more likely to click on" (Lee, 2009, p. 519).

To date, studies have demonstrated the value of PCs as a domain in which to conduct psychological and social science research—even though much research still remains to be done. Although we have provided a first literature review, we highly encourage researchers to enhance our theoretical and practical understanding of the origins and effects of PCs.

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