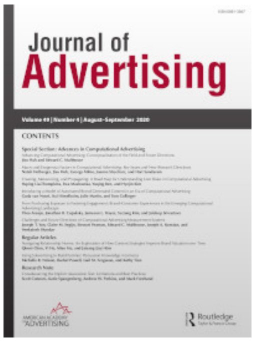

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Creating, Metavoicing, and Propagating: A Road Map for Understanding User Roles in Computational Advertising

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ABSTRACT

Over the past two decades, everyday users have become a prominent force in the advertising landscape. They actively participate in conversations with and about brands by creating, amplifying, and interacting with brand-related messages. These user activities generate large volumes of structured and unstructured data that advertisers can mine to understand consumer interests and preferences. In this article, we survey insights from the user-generated content literature through the computational advertising lens to offer a road map for future research. Specifically, we discuss three roles that users play—as creators, metavoicers, and propagators. For each role, we present key research areas that can benefit from a computational approach, identify the opportunities and challenges, and propose questions for future research. We also discuss the practical implications of applying computational methods to study users and user-generated content for advertisers.

Over the past two decades, a new force has risen to prominence in the advertising landscape. This force of everyday users is disrupting both how brand messages are created and how they are delivered to consumers. Instead of being passive recipients of brand messages, today's users are actively participating in conversations with and about brands by creating, amplifying, altering, and sometimes refuting brand-related messages. The power of users in this dynamic environment is already evident from existing research. For example, user-generated content has been shown to significantly affect brand choice and sales (e.g., Grewal, Stephen, and Coleman 2019). The rise of active users has created a corresponding shift in the role of advertisers. Rather than simply designing and broadcasting branded communication to consumers, a key job for advertisers now is to stimulate, guide, and facilitate brand-related conversations with and among consumers (Maslowska, Malthouse, and Collinger 2016). Together, users and advertisers are now intertwined in a two-way dynamic relationship, which has been likened to a pinball game (Hennig-Thurau et al. 2010) or a reverberating echoverse (Hewett et al. 2016).

The shifting landscape with active users brings exciting opportunities as well as unique challenges to computational advertising, an emerging multidisciplinary field which uses computing technologies and mathematical models to facilitate efficient, profitable delivery of advertising (Yang et al. 2017). On one hand, the unprecedented volume of data created by active users offers advertisers incredibly rich insights into the individual and collective mindset. These data can facilitate effective personalized advertising (Yang et al. 2017). On the other hand, fully unleashing the insights from data proves challenging, as methods for

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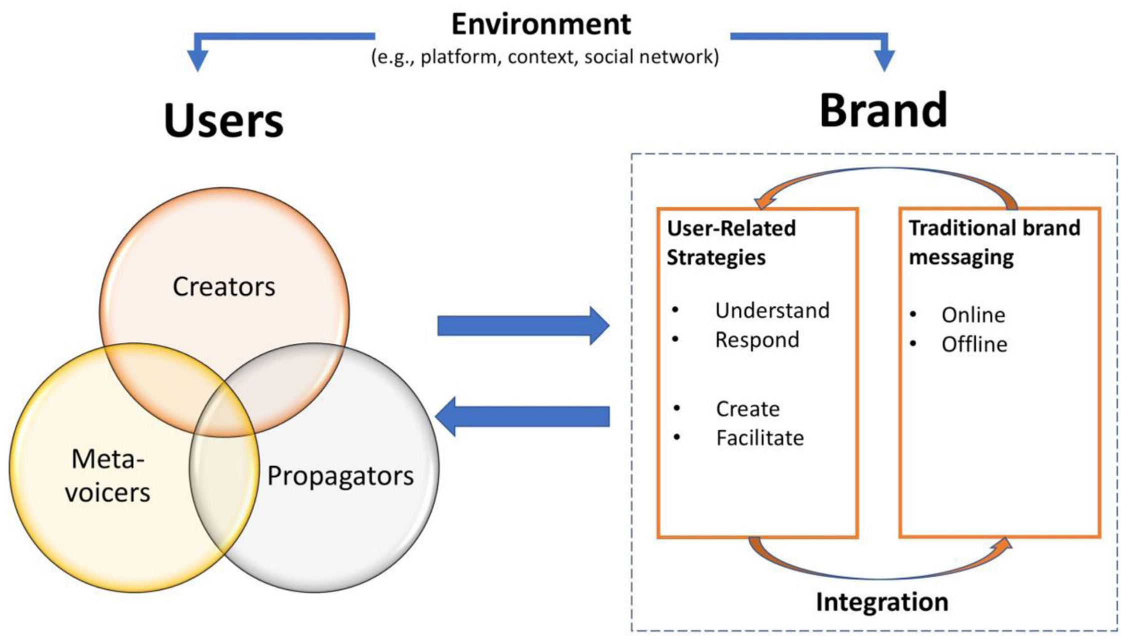

Figure 1. A conceptual framework for user–brand relationships in advertising.

analyzing such data are still emerging. While some data such as review ratings and likes are easily quantifiable, most user-generated content is unstructured, such as texts, rich media, and social networks. Extracting insights from these unstructured data requires advanced methods, such as text mining and machine learning (Dragoni 2017). In addition to the large volume of data, the active roles taken by users also increase the complexity of brand–consumer interactions beyond the relatively linear relationships of the past. There are often circular feedback loops between advertiser campaign efforts and user actions that feed and influence one another. Advertisers need help navigating these interactions efficiently and effectively to leverage the full power of users.

To this end, our article outlines research opportunities for using computational advertising to better understand and leverage users in advertising. Through this discussion, we aim to make two contributions. First, the field of computational advertising to date has predominantly focused on online advertising targeting and delivery (Dave and Varma 2014) and has paid limited attention to users beyond their role as potential customers. Addressing this gap, we identify the main research themes and future research questions related to active users and discuss the strategic implications of active users from a computational advertising perspective. Second, to guide the discussion, we present an organizing framework around three roles played by active users as creators, metavoicers, and propagators. Each of these roles presents its unique set of data and computational challenges that warrant more in-depth investigation. Although these roles have been examined as individual themes in previous user engagement research (e.g., Muntinga, Moorman, and Smit 2011; Shao 2009), we recognize that a single user can play multiple roles at different times.

Organizing Framework

Figure 1 shows our organizing framework to understand user roles in the context of computational advertising. Instead of portraying every force in the complex user landscape, we focus on the elements most central to computational advertising.

Active User Roles

The two key players in our framework are the user and the brand. On the user side, three roles are pertinent to computational advertising. We identify these roles based on the distinct conceptual functions they represent and the different kinds of data they generate. The first role is that of a content creator, who contributes original or derived brand-related content, such as product reviews, images, and videos. The data generated through this role are typically qualitative, ranging from textual to multimedia data, and are rich with information.

The second role is as a metavoicer. A metavoicer does not create original content but adds his or her opinions in the form of expressing likes, comments, and ratings for the original content of others.

Metavoicers create a more reactive form of data that is often meaningful only when analyzed in conjunction with the original content. Many metavoicing actions can be quantified, such as the number of likes and average ratings, but metavoicing in the form of comments can also generate qualitative data.

The third role is a propagator, who functions as a carrier of others' messages through sharing activities. The data generated by propagators are quite unique in that they are intertwined with data on the underlying social networks of which the propagating user is a part. The decision to propagate (or not) and to whom is often jointly determined by the nature of the content as well as social network properties.

We would point out that each user can play multiple roles. For example, a user can be a creator of his or her own content and a propagator of others' content; or the user may both create content and comment on others' content. In the most active case, one user can play all three roles. These multirole users are represented by the overlapping regions of the circles in the figure. In addition to the three active user roles, users can also play a more passive role in the form of content consumption. While we acknowledge that passive content consumption is a behavior assumed by many users, in this article we focus on active user roles. The role of a passive user, or a user as a passive content consumer, is similar to consumption of traditional ads or other brand-generated content, which has been well covered in the existing literature (cf. van Noort et al. 2020).

Brand Activities and Brand–User Relationships

On the brand's side, advertisers engage in two interconnected sets of activities. One set is traditional brand-controlled messaging both online and offline. This includes TV advertising and search marketing. The other set comprises activities around user actions, such as creating content to engage users, listening to social chatter, or proactively influencing and facilitating brand-related conversations. These two sets of activities form a feedback loop and should be integrated to form an effective advertising strategy. Much of computational advertising has focused on the traditional ad serving side (Dave and Varma 2014). We focus our attention on the user-related strategies side and on the challenges of integrating the two sets of activities.

Reflecting the reverberating nature of the environment, the actions by each player in our framework can affect those of the others, creating an infinite loop of spiraling effects. Sometimes these effects can be synergistic, with each side amplifying the other and converging toward a similar point of view. For example, users and a brand can join forces to support a common cause. Other times the two sides can hold divergent opinions and become antagonistic. In extreme cases, it can evolve into a full-fledged brand crisis. The dynamics between users and brands ebb and flow over time, shaping the overall brand story. These interactions can have consequential economic impacts both in the short term (e.g., sales) and in the long run (e.g., brand equity). It is also worth noting that the actions of brands and users do not occur in a vacuum. Instead, they are affected by the context of the interactions, the goals of the parties involved, and the platform on which the actions take place. These contextual factors need to be considered to understand user-generated content and related actions (cf. Helberger et al. 2020).

In the following sections, we discuss the three active user roles in detail, followed by the strategic issues facing advertisers. Rather than conducting a comprehensive literature review in each area, we focus on issues more relevant to computational advertising and on emerging areas that need more attention. Our primary goal is to stimulate new thinking about how these areas can be better understood by applying computational approaches and to identify future research ideas that will help advertisers unleash the power of users through computational methods.

Users As Creators

Users as creators generate their own brand-related content. These creators include not only customers but also other stakeholders, such as influencers, media, other brands, and political actors. Considering these other actors is important because they can affect how customers understand, redesign, and create advertising. They can affect one another not only at an individual level but also as a group, creating potentially simultaneous and indirect influence on advertising effectiveness.

Among the three user roles, creators represent the highest level of brand-related activeness (Muntinga, Moorman, and Smit 2011) and engagement (Malthouse, Vandenbosch, and Kim 2013; Maslowska, Malthouse, and Collinger 2016), as these users take the initiative to participate in a creative process or generate their own content. Behaviors displayed by creators have been called creating (Muntinga, Moorman, and Smit 2011) or producing (Shao 2009). Creators do not necessarily produce completely new content; they may participate in activities initiated by others, such as product or advertising codevelopment.

The content created by consumers generates huge amounts of data. Computational advertising's "approaches to expressively represent a rich set of advertising objects and environments, model and analyze complex stakeholder behaviors" (Yang et al. 2017) makes it well suited for analyzing such data. Advertisers can monitor and evaluate creators and their content—at a scale that was not possible previously—to (1) understand and predict creator motivations, (2) analyze user-generated content, and (3) quantify the results of creating behaviors.

Creators and Their Motivations

Previous research has investigated the characteristics and motivations of content creators (for an overview, see Christodoulides, Jevons, and Bonhomme 2012), often applying uses and gratification theory (see McQuail 1983). For example, Muntinga, Moorman, and Smit (2011) studied motives driving the creation of brand-related content on social media; and Hennig-Thurau et al. (2004) measured drivers of electronic word of mouth (eWOM). Some other factors examined were cultural values (e.g., Kitirattarkarn, Araujo, and Neijens 2018) and brand loyalty (Schivinski et al. 2019). Most previous studies into content creators have applied surveys or a mix of qualitative and survey methods (e.g., Daugherty, Eastin, and Bright 2008). However, in computational advertising, the creating behaviors examined are larger in quantity and more diverse in format, thus calling for other methods to investigate them.

Research applying computational methods to identify and understand creators' motivations is scarce, even though computational approaches to motivation have been discussed, for example, in microfinance (Liu et al. 2012) and robotics (e.g., Oudeyer and Kaplan 2007). Social scientists have applied computational methods to better understand and predict consumers' personalities as well as consumers' responses to ads (e.g., Matz and Kosinski 2019). IBM Watson uses linguistic analytics to infer personality characteristics, consumer needs, and values from various digital traces such as e-mails, blog posts, tweets, and forum posts.[1] In a similar vein, computational approaches can be used by advertisers to gain insights into other consumers' characteristics, such as attitudes, beliefs, motivations, and intentions. Advertisers can use AI-empowered tools to uncover hidden patterns of behaviors.

Future Research Questions

Computational approach allows us to answer new questions regarding creators. First, qualitative or survey methods dominant in existing research are useful for uncovering explicit drivers but may miss reasons that are more implicit (i.e., consumers are unaware of them) or difficult to articulate. These traditional methods are also difficult to scale up. Computational methods can be used to infer the less explicit drivers at a larger scale. To do so, the field needs to develop valid computational measures of motives as well as other constructs such as attitude. Some work has started in this area. For example, Yun, Pamuksuz, and Duff (2019) tried to computationally investigate brand attachment, and Roy et al. (2017) developed a computational trust measure using Twitter data. Still, we need more systematic efforts at developing valid and reliable computational measures of existing constructs.

Second, creators work in interactive networks where they are motivated and evaluated by others. While general social motivation is often included in previous studies, the interactive dynamics of constant feedback that can impact content creation are often neglected. This is not surprising, as directly measuring the iterative influence that takes place in complex environments is challenging. Computational approaches can offer some help here by analyzing the large quantities of content available online over time, similar to previous work that studied the temporal and social dynamics of online product reviews (Godes and Silva 2012; Moe and Trusov 2011).

Third, AI is changing consumers' behaviors, in that it can nudge them about their behaviors (e.g., screen time) or improve their decision making (e.g., recommend products). Consumers increasingly implement new technologies, such as voice assistants, virtual reality, and 3-D printers. They often interact with brands and other consumers through those devices. However, we still do not understand how these new technologies affect consumers' engagement with brands through creating behaviors. Future research should try to understand consumer brand experiences and their engagements with brands in the context of new, often AI-empowered, technologies (cf. Araujo et al. 2020).

Finally, today's content creators are not always humans. Increasingly, bots and other AI-enabled agents are not only distributing but also creating content. How do we recognize such content creators? How do we investigate the motivations of humans who develop these artificial content creators? These are interesting questions for future research.

What Do Users Create?

To better understand content creators and their activities, we need to investigate not only who creates and why but also what is being created. Previous research, mostly qualitative, has examined the different types of brand-related content that users create. For example, Smith, Fischer, and Yongjian (2012) compared brand-related, user-generated content across social media platforms, while Ertimur and Gilly (2012) used netnography and in-depth interviews to study user-generated ads. Some previous studies have also tried to describe user-generated content on various dimensions. For example, Vermeer et al. (2019) categorized consumers' posts as different eWOM types. Yang, Ren, and Adomavicius (2019) classified consumer complaints on Facebook business pages into those about product quality; price and money; and social or environmental issues. Still, there is no consensus on how we should categorize consumers' creations.

Recent studies have started to apply computational approaches to investigate user-generated content on a bigger scale, with a primary focus on topic and sentiment. For example, Liu, Burns, and Hou (2017) used latent Dirichlet allocation to analyze topics of consumers' interactions with brands on Twitter. Okazaki et al. (2015) used machine learning to analyze brand-related tweets and identified three forms of eWOM: objective statements, subjective statements, and knowledge sharing. Besides content topics, researchers have also examined sentiment as another important dimension of text. For example, the Liu, Burns, and Hou (2017) study mentioned previously also examined sentiment and found differences in sentiment within and across industry sectors.

While studies exploring textual user-generated content are growing, research investigating user-generated rich media is still in its infancy. Various categorizations of images have been proposed (e.g., Khosla, Sarma, and Hamid 2014; King 2015), yet research investigating different types of photos or topics presented in photos is very limited. One example is Kaiser et al. (2019), who studied 44,765 Facebook photos from 503 Facebook users in the United States and Germany. They found that uploading photos containing a brand name or logo is an indication of brand love, loyalty, and endorsement. The researchers further developed a machine-learning algorithm that can predict users' brand responses from their brand photos on Facebook. Similarly, computational analyses of user-generated videos are less developed. Hautz et al. (2014) studied user-generated videos in an experiment, showing that the effects of user- versus agency-generated videos on viewers depend on the quality of the video. Furthermore, videos generated by users were rated more positively than agency-generated videos when it comes to source expertise.

Future Research Questions

Computational research analyzing user-generated content is growing, but there are many open questions when it comes to the type of content being analyzed. First, the content of user-generated rich media is poorly understood. Yet such visual-oriented content is quickly increasing in social media, with users uploading more than 350 million photos daily to Facebook alone (Kaiser et al. 2019). Besides images and videos, users can create other types of content such as games and offline activities for online sharing. Emerging, often AI-empowered technologies may further open new frontiers for user creations. Fortunately, while still limited, tools enabling visual content analysis (e.g., Google Cloud Vision API, Microsoft Computer Vision) are becoming more available. Soon we should be able to investigate questions about visual-oriented content, such as the following: Can nontextual content reveal underlying consumer insights that are not available from explicitly expressed feelings in textual content? What do images, videos, and games created by users tell us about their attitudes and intentions regarding a brand?

Second, for advertisers to spot relevant consumers to reach out to, they need to identify content relevant to their brand, which remains challenging. Although we can use the brand centrality of a message, it ignores content that does not address the brand directly but may still prove relevant. Matters get even more complicated with the increasing amount of fake content and fake users/accounts (e.g., Collins and Frenkel 2018; Yun et al. 2020). Understanding the content of misinformation, such as fake news, ads, reviews, and videos, may bring us a step closer to devising effective coping strategies.

Third, content is increasingly created by consumers representing different cultural backgrounds and/or countries. Previous studies have compared content created by consumers with different cultural backgrounds (e.g., Ren et al. 2020), but this line of research is preliminary and often conducted using manual coding. Future computational methods may help researchers analyze big quantities of data from different countries, expressed in different languages and cultural connotations. For that, further development in natural language processing, particularly when it comes to non-English languages, is needed. This may allow advertisers not only to compare users across cultures but also to develop culture-sensitive strategies to address users.

The Impact of Creators and Created Content

Our understanding of the impact of organic communication is limited (for discussion, see Fulgoni 2015). It is clear that user-generated content can affect those who consume the content. Experimental studies show that brand-related user-generated content affects consumers' emotional and cognitive reactions, which subsequently affect behaviors (Kim and Johnson 2016). The exact impact of such organic communication may depend on the motivation behind the content (e.g., Ertimur and Gilly 2012) as well as the content itself. For example, as Bakhshi, Shamma, and Gilbert (2014) showed, social media posts which feature photos with a person's face are more likely to receive engagement than those which do not. Researchers further found the use of images in general increases subsequent sharing (Soboleva et al. 2017), but this effect depends on whether the images are more action or information oriented (Ordenes et al. 2019).

The activities that creators engage in can affect not only other consumers but also the creators themselves. For example, creation behaviors that trigger elaboration about the brand and how it contributes to a personal goal are more effective than creation behaviors irrelevant to the brand and personal goals (Malthouse, Calder, and Vandenbosch 2016). Christodoulides, Jevons, and Bonhomme (2012) found that creators' involvement with content generation can positively affect consumer-based brand equity.

Future Research Questions

The impact of user-generated content in the form of online reviews has been widely studied in previous research. But similar analyses of other types of user-generated content have trailed behind and need to be the focus of future research. What cognitive, affective, and behavioral changes can user-generated content bring about? What creator and content factors can make a piece of user-generated content impactful? Answering these questions will likely involve the use of both computational approaches and traditional advertising research methods.

Regarding creators, advertising scholars need to devise ways to identify both the economic and noneconomic value of content creators. This may be especially critical in certain contexts, such as political advertising, and may have a significant influence on advertising strategy. Not all creators bring positive value to the brand. Sometimes a creator may prove detrimental to the brand—for example, by spreading rumors. The value of a creator may also not always correspond to the valence of the content the user creates. For example, what starts as a negative rumor may translate into a positive brand story once the entire network's actions and reactions have been taken into consideration. Such scenarios suggest that the quantification of a creator's value may be context specific and should be considered in the setting of the social network in which the creator is embedded.

Users As Metavoicers

In online advertising, users can also play the role of a metavoicer. The term *metavoicing* was first coined by Majchrzak et al. (2013) to refer to the act of "reacting online to others' presence, profiles, content and activities" (p. 41). It is a unique capability of social media, which allows users to conveniently and quickly provide feedback and highlight the perceived value of the original content. These actions are called metavoicing because users' reactions add metaknowledge to the original content. Such metaknowledge can help other users, especially those who have not viewed the content, to assess the potential value of the content and whether they should engage with it. Metavoicing can take many forms, including likes, comments, reactions, replies, favorites, and up/down votes.[2]

While users can add metavoice to both brand-generated and user-generated content (Brodie et al. 2013), we believe metavoicing adds greater value to user-generated content for two reasons. First, there is generally a much greater volume of user-generated content than brand-generated content (Yang, Ren, and Adomavicius 2019), and user-generated content has been shown to affect consumer attitudes and purchase behaviors more (Goh, Heng, and Lin 2013). Second, compared to brand-generated content, there is greater variance in the quality and relevance of user-generated content. Hence, metavoice data, such as number of likes, votes, or comments, serve as an instrumental signal to help users find what is useful and relevant (Wang, Butler, and Ren 2013). In the rest of this section, we discuss different types of metavoicing actions, motivations behind such actions, and the effects of metavoicing on individual responses to brand- and user-generated content.

Characteristics of Metavoicing Acts and Metavoicers

Not all metavoicing acts are created equal. For example, although most prior studies have treated liking and commenting as similar engagement measures (e.g., Cvijikj and Michahelles 2013; Lee, Hosanagar, and Nair 2018), recent work has begun to conceptually differentiate between the two (Yang, Ren, and Adomavicius 2019). Engagement behaviors can be characterized along three dimensions (Brodie et al. 2011): the level of *cognitive* effort required (Oestreicher-Singer and Zalmanson 2013), the *emotional* states expressed, and the *behavioral* manifestation (Brodie et al. 2011). Liking and commenting differ in at least two regards: the level of effort required and emotional complexity. Liking is a "lightweight, one-click feedback action" (Scissors, Burke, and Wengrovitz 2016, 1501), whereas commenting is a deliberate form of "composed communication" that takes time and cognitive capacity to compose (Swani, Milne, and Brown 2013). In terms of emotional complexity, liking is mainly used to express positive and affirmative emotions such as agreement or acceptance (Scissors, Burke, and Wengrovitz 2016), whereas commenting can convey more complicated emotions such as disagreement, anger, or a combination of multiple emotions.

Future Research Questions

Existing research has focused primarily on metavoicing acts rather than on metavoicers themselves. Computational methods can be used to characterize metavoicers and heterogeneity among metavoicers. Some metavoicers can be powerful influencers, whereas others are ordinary users (Hennessy 2018). Some are selective about the content to which they add their metavoice; others may be less so. To make matters more complicated, many metavoicers are bots, in other words, automated software programs that can send messages and interact with users. The prevalence of bots and fake accounts has become a "dirty and open secret of social media."[3] For example, Twitter bots can tweet, retweet, like, follow, and unfollow other users. As a result, a significant portion of metavoicing may be the voices of bots and not real human users. Computational approaches are needed to automatically identify and isolate fake accounts, quantify the economic impact of fake accounts, and devise actions for curtailing the negative impact.

Another way in which advertisers can leverage rich metavoicing data is to use them as metrics to assess advertising effectiveness. While the common practice is to simply count the number of likes, comments, fans, and followers, the same count may have different meanings. For example, different types of metavoicing may carry different weights. It may also matter who liked, commented, or followed (e.g., a potential customer versus a loyal customer). New composite measures need to be developed to better capture the various goals that advertisers aim to accomplish, for example, to identify engaging content for further promotion or to identify common customer grievances.

Antecedents to Different Metavoicing Acts

Prior research has examined antecedents to metavoicing on both brand-generated and user-generated content, mostly in the context of Facebook business pages. For example, Lee, Hosanagar, and Nair (2018) analyzed 106,316 brand-generated posts on Facebook and found that brand personality (e.g., humor and emotion) had greater effects than informative content (e.g., price and deals) on the number of likes and comments the posts received. Yang, Ren, and Adomavicius (2019) analyzed 12,000 user-generated posts on Facebook business pages and found that likes and comments have different antecedents (e.g., positive posts attracted more likes but fewer comments). Their follow-up survey suggests that users like posts on Facebook mainly because of agreement or shared experiences, whereas users comment because they want to share their own experiences or answer other users' questions. Prior research also shows dynamic interplays among different metavoicing features. For example, the introduction of the reaction buttons on Facebook changed the use of likes and comments and caused a "rich getting richer" phenomenon in terms of user engagement (Yang, Ren, and Adomavicius forthcoming).

Another stream of research has examined what factors affect the helpfulness ratings of online product reviews. Two sets of antecedents have been examined: linguistic features of the review (e.g., subjectivity, informativeness, and readability) and characteristics of the reviewer (e.g., location and past review history). In general, reviews (1) that have both objective and subjective content and (2) reviews that are unequivocal, more informative, and readable tend to attract more helpful votes (Ghose and Ipeirotis 2011). In addition, reviews with descriptive information about the reviewer tend to attract more helpful votes (Forman, Ghose, and Wiesenfeld 2008; Ghose and Ipeirotis 2011). Information about the reviewer possibly serves as a heuristic for assessing the quality of the information and helps establish the reviewer's reputation.

Future Research Questions

Future research needs to continue to understand users' decisions to engage in different types of metavoicing behaviors. For example, when a user decides to engage with a post, which metavoicing features (e.g., like, comment) does the user choose? What factors affect the decision? The answers may depend on the contexts in which users make these decisions, such as whether it is in a network of friends or in a brand-hosted community with other users. While friendship and reciprocity may play a key role in the former, content sentiment and characteristics may matter more in the latter.

Another future direction is to use machine learning to mine a user's metavoicing actions to infer his or her interests, preferences, and brand loyalty. The essence of computational advertising is to find the best match between a user in a given context and a suitable and personalized advertising message (Broder 2008): the more that advertisers learn about a user, the more relevant their ads will be that target the user. While the content that users create can be mined for such purposes, many users post only sporadically, if at all, which limits the amount of available data. In contrast, users engage in metavoicing with much greater likelihood, frequency, and variety. Computationally mining metavoicing data can generate richer individual-level insights for serving relevant ads than mining creation data.

The Impact of Metavoicing Acts

Three lines of research have examined the impact of metavoicing. The first line examines the impact of the act on users who treat it as a sign of content popularity. Intuitively, positive metavoicing should bolster the impact of the content, whereas empirical evidence has provided mixed support. For instance, increased helpfulness of online reviews was shown to increase product sales in Forman, Ghose, and Wiesenfeld (2008), but such reviews reduced sales in Ghose and Ipeirotis (2011). Hence, having favorable metavoicing is not necessarily correlated with improved product sales or other economic impact.

The second line of research examines the impact of metavoicing on the metavoicer, and the effects seem to depend on the motivation and context of the metavoicing action. Users who have "organically" liked the page or voluntarily chosen to like the page often have positive attitudes toward the brands and are more likely to purchase (Mochon et al. 2017). After controlling for this self-selection bias, the mere gesture of liking a brand on Facebook had no effect or even a mild negative effect on customer attitude and purchase likelihood. There is also evidence that advertisers can harvest greater benefits when they use Facebook pages as a platform for firm-initiated communications instead of consumer-initiated social interactions (Mochon et al. 2017).

The third line of research examines the vulnerability of metavoicing to biases and manipulations. Essentially, metavoicing reflects the wisdom of crowds (Surowiecki 2004); that is, under the right conditions, many ordinary people can make better decisions than a few experts. One such condition is a decentralized and independent decision process without being influenced by a central authority or other people's opinions. When this condition is violated, the collective decision is likely to be biased and may even lead to irrational herding behaviors. Muchnik, Aral, and Taylor (2013) showed that a single, randomly given upvote or downvote right after content is posted can swing subsequent votes. The single upvote created "a positive social influence bias" and increased the comments' final ratings by 25% (p. 49).

Future Research Questions

Computational methods can help analyze and quantify the circular relationship between advertising campaigns and user behaviors. For instance, which users should advertisers target in a campaign to increase social media engagement. For example, should they ask them to like or to comment? What criteria should be considered in making the selection? As algorithms track and analyze targeted users' responses, the selection criteria can be further refined. Similarly, advertisers can take actions to encourage and cultivate user-generated content (e.g., a product photo contest on Facebook pages) and brand-cultivated content can lead to additional user engagement. Advanced algorithms are needed to capture not only the first-order effects but also second-order or even third-order spillover effects of advertising campaigns.

Future research should also continue to understand the social influence and bias associated with metavoicing acts. Individual consumers in modern society are constantly inundated with information about what to buy, where to eat, how to vote, and so on. Metavoicing adds another layer of information, which redirects attention. While one study has shown that users tend to herd on positive opinions and are skeptical of negative opinions (Muchnik, Aral, and Taylor 2013), depending on the circumstances, we may also observe negative herding behaviors. What roles do algorithms and bots play in facilitating or curtailing human herding behaviors? Future research should study both the design of these algorithms and human interactions with them. What happens when users become more aware of the algorithmic influence? How do human perceptions of the algorithms affect people's behaviors?

Users As Propagators

The third role, users as propagators, reflects users' ability to serve as an intermediate content broadcaster. This type of user is not an original source or creator of information but rather a transmitter of secondary information received from others (Hornik et al. 2015). They "propagate" secondary information to their social network by forwarding it or using sharing functions on social media platforms (Munzel and Kunz 2014). In this sense, propagators take on dual roles—recipients *and* sources of information—as information hubs. The information they forward usually involves advertisements, commercial editorials, brand-generated content, consumer conversations about brands, and secondary information (Hornik et al. 2015).

Propagators generate unique data for computational advertising research. Propagation often occurs through massive online social networks, the properties of which require computational approaches to unravel. Propagation is also driven by the massive amount of content that is shared by users every day. Successful propagation is often the result of both the content and the network. However, as our brief discussion of the literature will show, most research on propagation has considered these as separate areas rather than jointly.

Motivations Behind Propagation: An Untapped Computational Area

There has been extensive research on the motivations behind eWOM propagation, although most studies have relied on traditional social science methods such as surveys and experiments. These studies have identified both intrapersonal and interpersonal motivations of propagation. For example, the key drivers of e-mail forwarding were perceived importance, value, and information quality of a viral e-mail (Phelps et al. 2004), recipients' social capital (José-Cabezudo and Camarero-Izquierdo 2012), and close interpersonal relationship between the sender and the recipient (Chiu et al. 2007). Similarly, in user conversations about a brand, the key motives were tie strength, interpersonal trust, normative influence, and informative influence (Chu and Kim 2011; Hu and Yang 2015). For viral advertising forwarding, the common motives were expected benefits of sharing and the propagator's relationship with the brand (Hayes and King 2014; Hayes, King, and Ramirez 2016).

Future Research Questions

Like the motivations behind content creation, the question of why users propagate has seldom been answered using computational approaches. This may be partly due to motivation being an abstract psychological concept, which is easier to measure using self-report methods but harder to characterize with behavioral proxies (Roy et al. 2017). Yet a computational approach can advance the understanding of user motivations in propagation, as its unique advantages allow researchers to investigate the behavioral manifestations of such concepts shown by a massive number of actors in a networked setting (Roy et al. 2017).

Furthermore, previous studies using traditional social science methods have approached propagators' motivations in an egocentric fashion, treating propagators as the central actors in a one-to-one or one-to-many setting. With the aid of computational approaches, future research can explore how the quality and quantity of community-level behavioral interactions among users differently drive propagation. For example, an online community having an active posting/responding culture among community members might engage in more message propagation than one led by a few opinion leaders or administrators. Advertisers can induce more effective spreading of their messages by capitalizing on community-level interactions. In doing so, computational approaches, such as social network analysis and iterative algorithms based on behavioral data, can enable advertisers to understand the chain of interactions among a massive number of connected users online.

Content Factors That Drive Propagation

The second research area focuses on the types of message content that elicit propagation behaviors. Unlike research on propagation motivation, a great deal of research on content factors has leveraged computational approaches with large amounts of data (e.g., Aleti et al. 2019; Araujo, Neijens, and Vliegenthart 2015; Cvijikj and Michahelles 2013; Soboleva et al. 2017). Some studies have investigated the characteristics of brand-generated social media posts that led to propagation. For example, tweets with informational cues tended to induce a greater number of retweets; and when emotional cues and traceability cues (i.e., hashtags) were added to informational cues, it led to even more retweets (Araujo, Neijens, and Vliegenthart 2015). In the context of brand-generated Facebook posts, entertainment posts and rich media posts led to greater sharing (Cvijikj and Michahelles 2013).

Linguistic types of social media content were also explored. Using dictionary-based automated text analysis, Aleti et al. (2019) classified the tweets posted by influencers into five different types (i.e., internal analytical, external analytical, external narrative, internal narrative, and angry outburst). Among the five types, the study found that the highest retweets were associated with externally focused tweets (i.e., tweets with heavy use of second-person singular noun *you* and first-person plural pronoun *we*) and narrative-style tweets (heavy use of adverbs, auxiliary verbs, conjunctions, negations, and personal pronouns). These findings indicate the importance of message framing strategy in propagation.

Future Research Questions

Previous studies in this area have focused primarily on analyzing positive social media data initiated by brands or endorsers. The propagation of negative user-generated content about a brand needs further research. A key question is how propagation works when the information is false, maliciously manipulated, or unsubstantiated. Such topics have received scholarly attention in other domains such as health and politics (e.g., Al-Rawi, Groshek, and Zhang 2019). However, research on this topic in advertising is still rare, despite such information's ability to critically harm a brand's reputation and its relationship with consumers. This is a good direction for future research, and computational approaches like machine learning can help provide automated and speedy identification of such content and help design effective countermeasures.

For most brands, mere propagation is not an end goal but a means to spread the persuasive power of messages. Recent research suggests that content propagation and purchase may be driven by different factors, and message cues that encourage propagation may not always lead to more successful conversion (Sun, Viswanathan, and Zheleva forthcoming). Future research should consider multiple relevant outcomes and identify the facilitating versus inhibiting message characteristics associated with each outcome. Massive field experiments in combination with computational methods may be particularly useful in establishing causal relationships.

The Impact of Propagators As Information Sources

The third area of research focuses on how the characteristics of initial propagators affect subsequent message effects or the rest of the message diffusion process. Initial propagators are often referred to as *seeds*, meaning the first layer of users that disseminates the original content to others (Liu-Thompkins 2012). This line of research has been led by computational approaches, mainly based on social network characteristics. Some common characteristics of seed propagators included trustworthiness (e.g., Huh et al. 2020), network size, and topological position in a network (e.g., Araujo, Neijens, and Vliegenthart 2017; Hinz et al. 2011; Himelboim and Golan 2019; Liu-Thompkins 2012).

Studies have demonstrated the importance of social network size and position by applying computational approaches (e.g., social network analysis and computer simulation) to social media data. Analyzing viral videos from YouTube and the network structures of the video subscribers, Liu-Thompkins (2012) found that the most effective viral diffusion is achieved when a large number of initial propagators are used, when such seeds have strong ties with the advertiser and have a moderate amount of interest overlap among one another. Analyzing tweets from top global brands, Araujo, Neijens, and Vliegenthart (2017) found that influencers (e.g., public figures or celebrities) and information brokers (i.e., users who bridge two unconnected user groups) tend to induce more retweets if they first propagate brand-generated tweets. Similar patterns have been observed in viral campaign referrals (Himelboim and Golan 2019; Hinz et al. 2011). More recently, Huh et al. (2020) used Trust Scores in Social Media (TSM) Algorithm with Twitter data and confirmed the effectiveness of trustworthy seeds in initiating wider and speedier viral ad diffusion.

Future Research Questions

Many important computational research questions exist on propagators and their network structure. In particular, there is a great need to merge content factor considerations and network properties to identify the interaction and optimal pairing between the two. For example, powerful information sources used to relay brand-related rumor-clearing messages should have different characteristics from megadistributors of brand promotion messages. Future studies should develop new criteria for identifying context- and content-specific propagation seeds and hubs, and calculate the economic consequences of different criteria. Computational methods can combine network and content data to find innovative ways of identifying the right propagators for the right content and situations.

Future research should also examine ways of facilitating or impeding user-driven, naturally occurring propagations to generate optimal financial outcomes. One possible way of nudging toward widespread diffusion is to incentivize users as propagation seeds to trigger information cascade. Computational research approach can help us use sponsored propagators as channels of dissemination and closely monitor the whole dissemination process, similar to media planning. For example, when is the best day and time for sponsored propagation? How long should the propagation process continue? Who would be most susceptible to sponsored propagators? How can we incentivize propagators to disseminate across platforms for wider reach and exposure? Those are all promising research directions to pursue.

Integration and Strategy Issues

The changing roles of users as creators, metavoicers, and propagators require businesses to rethink their advertising strategies and plan for today's increasingly dynamic environment (Hewett et al. 2016). This adaptation ranges from deciphering the voices of customers, to effectively responding to user content, to proactively engaging users and facilitating user dialogues related to the brand. At a strategic level, advertisers need to consider how the new user roles should be integrated into existing strategies and transform their thinking, and how computational methods can yield insights to help optimize advertiser actions. In this section, we address the strategic issues at the intersection between active users and computational methods.

Understanding and Responding to Users

Brand-related content created and shared online by users represents a treasure trove of information that was previously difficult to obtain. Such information has been leveraged to derive a more accurate picture of brand sentiment shift by simultaneously considering sentiment of consumer postings and platform format (Schweidel and Moe 2014). Studies have also demonstrated the power of text mining in deriving relevant insights from user-generated content—for example, by extracting consumers' content preferences through a topic model of consumer search queries (Liu and Toubia 2018).

Besides listening to users, advertisers also need to respond effectively to brand-related content from users. One challenge is in determining *when* response is needed, as sifting through lots of user content can be time-consuming. Computational approaches can help here. For example, Vermeer et al. (2019) used a supervised machine-learning algorithm to identify social media messages that warrant a response from businesses. They show that response-worthy messages are not always negative, which challenges the common practice of focusing more on negative consumer comments.

Another relevant question for social responding is *how* brands should respond in a given situation. Most research in this area has relied on controlled experiments to isolate consumer reactions to different response strategies. For example, Barcelos, Dantas, and Sénécal (2018) showed that the effectiveness of a human versus corporate voice in brand response depends on the type of consumer goals and the valence of the original consumer comment. Similarly, Johnen and Schnittka (2019) compared accommodative versus defensive responses to negative consumer comments and found that a defensive response is more suitable for hedonic contexts, whereas an accommodative response is better in utilitarian settings.

Future Research Questions

Despite recent advances, research on how brands can effectively listen and respond to user-generated content is still in its infancy. From a listening perspective, current work on identifying topics and trends in user-generated content is still crude. There are often substantial gaps between automated and manual analyses (Canhoto and Padmanabhan 2015). Future research can improve the effectiveness of listening by pursuing three directions. One, besides extracting individual topics, future research needs to capture the relationships *among* various topics reflected in consumer postings, which can reveal additional meanings and associations conveyed by users. Second, most existing works have been retrospectively focused. A more forward-looking approach is needed to identify emerging trends and to extrapolate future directions from retrospective content. Such forward-looking predictions can lead to competitive advantage for advertisers. Finally, manual coding used in existing machine-learning algorithms can be enriched with traditional qualitative studies of user-generated content. The rich insights derived can be leveraged to guide more meaningful automated concept extractions.

From a response perspective, future research needs to investigate brand responses to user content beyond complaints and brand crises, answering *how much*, *how*, *where*, and through *whom* (brand versus fans) to respond in a given situation. Such investigations should use larger-scale real-world data to validate insights from experimental studies. Moreover, determining the proper response to each comment quickly becomes implausible as a brand's audience grows larger. Automated-response mechanisms such as chatbots have been created for this purpose. But existing research warns against fully automated responses due to the loss of relational benefits derived from parasocial consumer–brand interactions (Labrecque 2014). Computational algorithms can ease the burden by offering a general direction on how to respond, possibly through an optimization scheme consisting of multiple possible response strategies.

Influencing and Facilitating User Conversations

Beyond reactive listening and responding, a proactive advertiser can actively facilitate user conversations and influence the nature of those conversations. Examining this dynamic loop between user- and brand-generated content, Hewett et al. (2016) show that having an active Twitter strategy can both reduce user eWOM volume and improve the sentiment of consumer reactions in a downward-spiraling environment (e.g., crisis). Traditional advertising, in contrast, did not affect user-generated content but had a direct positive impact on customer actions. This research provides clear evidence of advertisers' ability to proactively drive user conversations, but such effects may vary across businesses and tools used.

Two strategic questions are relevant to advertisers' proactive influence of brand chatter. The first is the optimal level of brand involvement. Too little involvement may make a brand appear apathetic, whereas too much involvement may be considered intrusive and lead to consumer reactance. An analysis of 10 online communities found that firm engagement has an inverted U-shaped effect on the sentiment of consumer postings (Homburg, Ehm, and Artz 2015). The challenge for each brand is locating the optimal point where firm participation creates the highest positive impact on consumer conversations.

Another important question is how brands can effectively influence both the likelihood of brand-related user dialogues and the content of such conversations. Most research in this area has approached the question from an information propagation perspective (e.g., Ordenes et al. 2019; Tellis et al. 2019). One example is Meire et al. (2019), who studied the interaction between brand-generated content and brand experience in driving the sentiment of user conversations. They found that while emotional brand-generated content is universally helpful in enhancing consumer sentiment, informational brand-generated content is more important when brand experience is negative.

Future Research Questions

Future research needs to move beyond the likelihood of brand chatter to study other content-related outcomes that brands can proactively influence. This may include the positivity of user conversations, aspects of the brand that users talk about, and the format in which users talk about the brand (e.g., images, videos).

Besides the diversity of outcomes, the scope of the outcomes can be also expanded. That is, can brand actions influence not only individual consumer reactions but also network-level outcomes? If so, how? Well-crafted brand messages that strategically target specific network nodes may lead to cascading influences on the entire network, creating new trends in user dialogues. A computational approach combining both content and network factors is needed to achieve such positive network-level influences and minimize unfavorable networkwide outcomes.

Finally, advertisers typically monitor what users say about their own brands. They are missing opportunities to identify vulnerabilities in competitors' networks. Computational research needs to examine simultaneously self–brand user conversations and user content about competitors to create benchmarks and study interbrand dynamics. Would proactively influencing a competitor's network of consumers require similar or different tactics as influencing one's own network? The possibility of such network "wars" may fundamentally change the competitive landscape and how brands approach competition. The macrolevel consequence and the ethics associated with waging such wars will need to be studied.

Integrating User Conversations into Firm Strategy

So far, we have focused on user-related issues. In reality, advertisers need not only to manage user dynamics but also to decide how to integrate user interactions into an overall strategy. One research stream deals with the relative impact of and synergy across paid, owned, and earned media. Among the three media types, users play a dominant role in earned media, while owned media represent a hybrid of firm and user activities. Across studies, owned and earned media are found to have significant impact on sales (e.g., Pauwels et al. 2016; Vieira et al. 2019), but the magnitude of the impact varied. For example, while Vieira et al. (2019) reported a higher impact of owned media than earned and paid media, Lovett and Staelin (2016) found paid advertising to have a larger impact for entertainment products.

The three media types differ in impact size, and they also play different roles. Lovett and Staelin (2016) show that while paid advertising primarily fulfills a reminding function, earned media increases the enjoyment of an entertainment product. Owned media in contrast has both a positive effect through reminding and a negative effect by reducing product enjoyment. Consistent with the idea of an echoverse, synergy exists across the different media types, and the extent of the synergy depends on how familiar consumers already are with the brand (Pauwels et al. 2016). Overall, it appears paid, owned, and earned media all have their places in a brand's advertising strategy, and the optimal mix likely depends on the industry, the brand, and the advertiser's goal.

Future Research Questions

More research is needed to help advertisers tackle the challenge of integrating user activities into their advertising strategy. A key consideration is how firms should balance between investment in brand messaging and user activities. Future research needs to create empirical generalizations and to move beyond a primarily descriptive approach to be more prescriptive (e.g., see Aravindakshan, Rubel, and Rutz 2015). Furthermore, user activities tend to be highly skewed, with a few users accounting for a lot of actions. Future research needs to investigate the unequal distribution of users across levels of activities and the economic impact of such a skewed distribution. Typically, it takes multiple exposures to an advertisement or a product for consumers to be convinced and converted into a loyal customer. Is it better for a small number of messages to harvest most attention, or is it better to have attention more equally distributed across more messages?

Besides finding the right balance between user and brand activities, future research also needs to address the integration of information from user social activities with traditional information that advertisers already gather (e.g., surveys, transaction records). Given vastly different data sources and formats, integrating such information to form a holistic view of customers will be a significant challenge. Future research needs to develop better methods for data matching, integration, and analytics, similar to what Feit et al. (2013) did with multiplatform media consumption data.

The diverse roles played by users further point to the need to revise how firms value their customers. Traditional customer lifetime value calculation based solely on sales and costs may be outdated. As Van den Bulte et al. (2018) show, consumers' social capital can be effectively translated into economic gain. How can social value from nonpurchase activities be integrated into customer lifetime value? Some researchers have started to address this question, such as Ho et al.'s (2012) formulation of customer value as the sum of purchase value and influence value. More research is needed to devise reliable measures of customer lifetime value that integrates both traditional economic values and values derived from users' social activities.

Conclusions

This article outlines key computational advertising issues that arise from the increasingly active roles that users are playing. Active participation of users in the advertising landscape has created a much richer and more complex environment for advertisers. Given computational approaches' ability to tackle a large amount of less structured data, it is both critical and desirable to integrate these methods into advertising research and practice. From an advertiser's perspective, our work suggests the need to step beyond programmatic advertising when applying computational methods. The potential from combining user strategies with computational methods is tremendous both strategically and economically. From a message perspective, advertisers can reduce creative costs by computationally identifying and leveraging user-generated content. The insights from analyzing the mass volume of user actions can also bolster the effectiveness of brands' own message design. From a media perspective, computational approaches can be used to identify efficient propagators of brand-related messages and users who can add credibility and persuasiveness to the messages. Computational analyses can also help identify unfavorable or false information early to mitigate the detrimental effects on brands. In conclusion, both opportunities and challenges exist in developing robust computational approaches to tackle user issues in advertising. We hope our work will guide and inspire future computational research on incorporating users into brand advertising efforts.

Notes

1. https://www.ibm.com/cloud/watson-personality-insights.
2. In this section, we exclude sharing actions (e.g., retweeting) from metavoicing. Those actions are considered separately in the next section on users as propagators.
3. https://knowledge.wharton.upenn.edu/article/twitter-and-the-bots.

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