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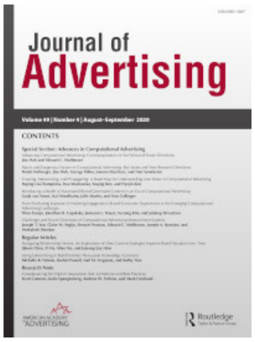

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Introducing a Model of Automated Brand-Generated Content in an Era of Computational Advertising

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ABSTRACT
Advancements in computing, technology, and their applications to advertising enable marketers to deliver brand messages tailored to individuals and consumer segments. The growth of computational advertising (CA) has created new opportunities but also poses risks in the use of algorithms to generate and optimize the impact of such messages. This article addresses a particular domain influenced by these advancements, namely, automated brand-generated content. We offer an automated brand-generated content (ABC) model that posits two advances. First, rather than solely optimizing consumer data for enhanced impact of automated content, we submit, and provide extra key variables to further illustrate, that there is a desirable balance of both consumer and brand data as inputs to algorithms to serve short- and long-term impact goals. Second, this article guides research by addressing tensions between understanding the relationship between inputs and desired impacts (both short and long term) and proposing a research agenda for future work.

Groundbreaking advancements in computing and technology are causing a paradigm shift in advertising. Algorithms and mathematical methods are at the center of these changes that enable computational advertising: the use of computing capabilities to analyze consumer behavior, tailor content, and facilitate the delivery of advertising information to (potential) consumers across media vehicles and touch points (Yang et al. 2017). Computational advertising (CA) changes the way brands generate and deliver their content. Previously, content was generated by marketers on behalf of their firms (e.g., Goh, Heng, and Lin 2013) or by creatives on behalf of advertisers, and it was the outcome of consumer insights provided by designated departments. Now, brand messages are often computer generated with minimal or no human interference and are increasingly based on consumer behavioral data (e.g., an individual's Web search and browsing history, in-store shopping behaviors tracked with loyalty cards, or words overheard by speech recognition devices). In addition—as with all things digital—content is delivered to the consumer across a growing number of touch points as the channels and diversity of media proliferate. Consumers can increasingly interact with content 24/7 because of connectivity in digital, virtual, and augmented media contexts.

In parallel with these changes in how brands generate and deliver their content, researchers and advertisers have increasingly focused on the automation of content to make it optimized for each consumer and have increasingly relied on data both as inputs for decision making (e.g., consumer interests based on

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online search behavior) and for measuring the impact of content (e.g., conversion rates). In this respect, previous researchers have argued that a central challenge for brands is to find the best match between consumers and content (e.g., Broder 2008; Dave and Varma 2014). We posit that more data do not always improve outcomes (e.g., Adomavicius and Tuzhilin 2005) and that the optimization of content is about balancing appropriate data inputs. Such data can range from "scarily detailed to practically nil" (Broder 2008, p. 1). If artificial intelligence (AI) lives up to its promise, computational methods should be able to sift through all available data and distinguish relevant from irrelevant data fully automatically. However, such automation is not the reality today, and research suggests that different types of data, other than behavioral consumer data that are most commonly used, can be relevant. In fact, research provides evidence that a range of consumer attitudes and perceptions (e.g., Boerman, Kruikemeier, and Zuiderveen Borgesius 2017) as well as brand data (e.g., Bleier and Eisenbeiss 2015) are important in optimizing content. Therefore, in contrast to previous research on data-driven content, which mainly relies on behavioral consumer data as inputs, we argue there is a desirable balance between both consumer data (including attitudinal and behavioral data) and brand data as inputs to algorithms that optimize content.

In measuring the impact of optimized content, current practices and research mainly consider short-term consumer responses (e.g., ad click rates). Impact measures, in terms of what the content does for the brand, especially in the long run, are generally disregarded. We posit that to measure the impact of optimized content, both short- and long-term impact measures should be taken into account, related to both consumer actions and brand value. Moreover, we argue that optimization can lead to a Faustian bargain by improving near-term responses to content at the cost of longer-term brand value; as such, there is a tension between shorter-term and longer-term impacts of automated brand-generated content.

In a communication environment increasingly influenced by computational methods, we introduce the automated brand-generated content (ABC) model to understand and explore the balance between consumer and brand data as inputs and discuss the tension between short- and long-term consumer and brand impacts as performance goals. In short, we propose this model to assist brands in thinking about the best way to automate content given their unique contextual constraints and objectives.

The ABC model's contribution is threefold. First, we aim to describe the current state of affairs within the communication environment, as it is increasingly influenced by computational methods. We introduce *automated brand-generated content* as the transformation of brand and consumer data into a message that is created and delivered with some level of automation. We discuss this concept through the lens of communication and advertising bodies of literature. Second, we extract key variables that determine the impact of automated brand-generated content on outcomes of interest. Third, we identify empirical gaps in understanding the relationship between inputs and desired impacts (both short and long term) to propose a research agenda for future work.

We begin this article by introducing the ABC model. For each element of the model, we review current practices and existing scholarship, thereby identifying gaps in understanding and areas of future research. Based on this discussion of the model, we propose a research agenda.

The Automated Brand-Generated Content Model

Our proposed ABC model considers the following key elements: (1) automated brand-generated content that aims to best balance (2) consumer data and (3) brand data in order to reach the desired (4) impact. The elements are part of a dynamic/iterative process: Content is created based on data. When such content is delivered, consumer responses toward the content can be measured. This response information is used to optimize subsequent content. More precisely, we suggest that automated brand-generated content is based on an interactive, technology- and data-mediated relationship (Vesanen 2007) between the brand and the (prospective) consumer. Such a dynamic process view is in line with suggested visualizations of 21st-century marketing communications (Schultz and Schultz 1998) and conceptualizations of personalized communication (Adomavicius and Tuzhilin 2005; Vesanen 2007; Vesanen and Raulas 2006; Strycharz et al. 2019a).

Our model is differentiated by the incorporation of brand considerations, whereas previous frameworks for the optimization of automated marketing communications have considered consumer data only as input and output variables (see Figure 2 in Adomavicius and Tuzhilin 2005; Figure 2 in Schultz and Schultz 1998; Figure 1 in Vesanen and Raulas 2006). Also, we propose to include consumer attitudinal and perceptual data as inputs to the ABC model,

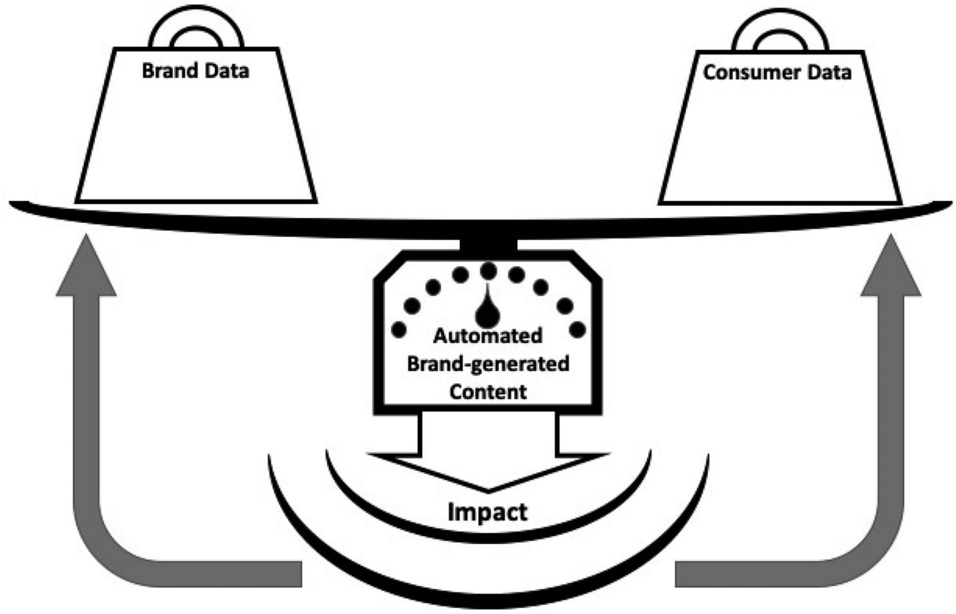

Figure 1. The automated brand-generated content (ABC) model.

while the current practice is to focus on behavioral data. Finally, we propose that impact should be measured not only in terms of direct responses to content (e.g., clicks, opens, likes) that reflect short-term impact but also in terms of long-term impact on the brand and consumer receptivity to—or disengagement from—automated content within the broader ecosystem. Next, current practices and academic research related to each of these elements are discussed, including empirical evidence of their interplay, providing implications for the model.

Automated Brand-Generated Content

In the ABC model, automated brand-generated content is the output of transforming brand and consumer data into a message that is created and delivered with some level of automation. To understand this phenomenon, we discuss the concept through the lens of advertising and communication literatures. We focus first on the "brand-generated" part of the concept, and then discuss the "content" and "automated" parts.

Brand-generated content is also referred to in the literature as "marketer-generated content" (e.g., Goh, Heng, and Lin 2013) or "firm-generated content" (e.g., Kumar et al. 2016). It entails content disseminated by the brand (i.e., being "an actual brand, or organization, person or cause," as described by Dahlen and Rosengren 2016, p. 337). Therefore, the brand is its source is why it intrinsically differs from the concepts of brand-related content and brand communication, as these concepts often encompass content generated by consumers as well (e.g., Muntinga, Moorman, and Smit 2011; for a discussion on the concept of brand communication in the domain of social media, see Voorveld 2019). Content that is brand generated is deliberately planned and distributed by the brand. As such, the concept is in line with recent definitions of advertising. For example, Knoll (2016) defined social media advertising as "persuasive and planned communication by advertising professionals" (p. 267). Similarly, Dahlen and Rosengren (2016) argue that advertising entails communications initiated, rather than paid for, by the brand. This also means that contents encompass messages placed not only in paid or third-party media but also in so-called owned media as well. This is why Dahlen and Rosengren suggested dropping the term *mediated* from the definition of advertising. Thus, content generated by the brand encompasses messages in owned and paid media; but it not does not entail communication about the brand. Therefore messages in earned media are excluded (Ashley and Tuten 2015).

Contents may range from completely tailored to the individual consumer to a completely generic brand message, depending on the weight that is given to brand versus consumer data in transforming these data into a message. Contents also have different values, faces (or formats), and delivery modes. Typical values include educating, informing, engaging (e.g., Gensler et al. 2013), reputation building (e.g., by addressing negative online consumer feedback; Van

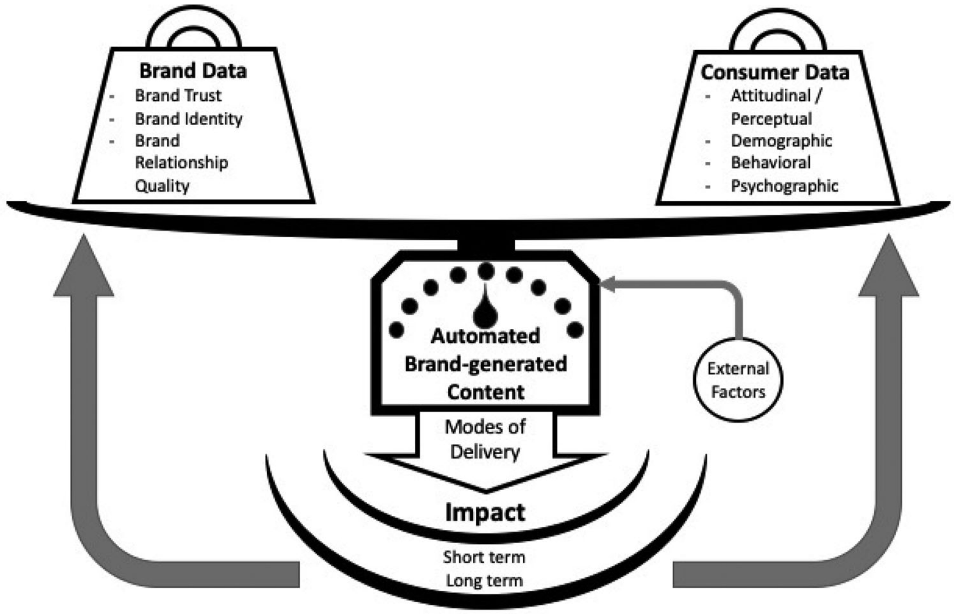

Figure 2. ABC research model.

Noort and Willemsen 2012), and, of course, sales. To exemplify, in the business-to-business marketing environment, along with specific calls to action to purchase, content addresses other values as well and may entail original research, white papers, opinion pieces in print, video, infographics, and audio (e.g., podcasts). Indeed, academic research examines a wide range of faces (or formats) of content, such as promotional product videos (e.g., Diwanji and Cortese 2020), advergames (e.g., Cauberghe and de Pelsmacker 2010), web care responses (e.g., Van Noort and Willemsen 2012), brand posts on social media platforms (e.g., Demmers, Weltevreden, and van Dolen 2020), brand websites (e.g., Voorveld, Neijens, and Smit 2009), e-mails (e.g., Kent and Brandal 2003) , location-based mobile messages (e.g., Bruner and Kumar 2007), newsletters and magazines (e.g., Müller et al. 2008), and chatbot conversations (e.g., Zarouali et al. 2018).

Technological advancements will continue to increase the number of faces of content—for example, resulting in more virtual, augmented, or dialogic content (e.g., chatbot content). Today, delivery channels (owned and paid media) for optimized content are websites (for online behavioral advertising), social media (for social media advertising), e-mail (for e-mail marketing), mobile phone apps (e.g., for notifications), and brands' owned websites (for website morphing based on preferences; Strycharz et al. 2019a). However, with technological developments in areas like speech recognition, virtual reality, and augmented reality, the modes of delivery are rapidly changing, allowing for continuous interactions (across touch points) between brands and consumers. As such, brand-generated content is evolving toward a continuous dialogue between brands and consumers. Clearly, such developments offer novel frontiers for brands to create content via an "infinite" set of media vehicles that are accessible to consumers 24/7.

Next, we focus on the automation component. This component relates to both the creation and the delivery of content. In the past, brand-generated content was the outcome of a creative process generated by marketers on behalf of their firms (e.g., Goh, Heng, and Lin 2013) or by creatives on behalf of advertisers; now, because of technological advancements, brand-generated content is often computer generated based on consumer data, with minimal or no human interference. In that sense, content is generated by a machine more so than generated by the brand. Second, automation also involves the delivery of brand-generated content. Since the late 1980s and early 1990s, information technology has greatly expanded the possibilities for message delivery, causing a growth in direct marketing (i.e., "a relational marketing process of prospecting, conversion, and maintenance that involves information feedback and control at the individual level by using direct response advertising with tracking codes"; Bauer and Miglautsch 1992, p. 10).

While third-party media has dominated the environment for brands to reach consumers for decades (Schultz 1998) in direct marketing, brand-generated content operated primarily as a method of engaging directly with end users, thus circumventing or avoiding third-party media (Hennig-Thurau et al. 2010;

Hennig-Thurau, Hofacker, and Bloching 2013). Historically, direct mail and telemarketing were the tools of the trade. More recently, digital media that allow for a direct dialogue with the brand are ways enterprises engage with their consumers. Such media include e-mails, short text services (e.g., Zhang, Kumar, and Cosguner 2017), brand web environments (e.g., Song and Zinkhan 2008), branded apps (e.g., Bellman et al. 2011), and social media channels (e.g., WhatsApp, Twitter; e.g., Araujo, Neijens, and Vliegenthart 2017). The delivery of content is also automated by programmatic advertising processes "through which media sellers and buyers align organizational processes with automation technology" (Winterberry Group 2013, p. 3).

Automated creation of brand-generated content does not come without challenges, as it can be seen as being at odds with the creativity element of content creation and, more broadly, with human input. Although machines are programmed by people with informed opinions, automation by default results in less human control and/or less control by those who oversee the brand. Tools for automated content creation are increasingly popular and, due to extremely rapid developments in AI, such tools are now used across stages of content strategy, including creation or generation, planning or scheduling publication of content, and monitoring of content performance. It is increasingly possible to create visual, audio, and text-based content with algorithms. With machine learning and deep learning techniques, machines can produce similar types of content or even entirely new types of content. For example, Google developed algorithms that turn text into pictures. The algorithm is able to generate images, based on textual input, that are significantly different from the images in the computer's initial training set. Other tools are semantic tools for automated text writing, audio content creation, or maintaining a consistent visual design across channels.

When using such tools for automated generation of content, content is less carefully crafted or generated by the brand, marketer, or creative involved. At the same time, it is argued that computers cannot be creative as humans are, that they cannot create real new content, and that they can only learn from the past and generate more of the same. Given that advertising literature has repeatedly demonstrated the importance of creativity for generating impact (e.g., Liu-Thompkins 2019; Smith, Chen, and Yang 2008), and even for tempering possible negative effects (e.g., such as intrusiveness; Kim 2018), one might argue that automated generation of brand content is detrimental in the long run. Academic research has not thus far isolated the impact of content being generated by computers, as compared to being human generated or human computer generated. Therefore, it remains unclear whether consumers will even notice the difference and, if so, whether they will think about the content differently. But it might be important to measure perceived creativity in the process of automated brand-generated content.

Implications for the ABC Model

Optimizing the creation of automated brand-generated content, then, should consider both consumer data (i.e., what we know about the consumer to whom we aim to deliver content) and brand data (i.e., the intrinsic characteristics of the brand) as inputs to achieve the desired impact. As automated brand-generated content is the output of transforming brand and consumer data into a message that is created with some level of automation, the most prominent challenge is balancing these inputs. The automated process should determine the selection and weight of the different data types (brand and consumer) that feed the content and subsequently the impact. The resulting optimized content can range from completely tailored to the individual consumer to a completely generic brand message. Perceived creativity should be considered as an impact measure, as its absence may have a detrimental effect on automated content.

Consumer Data

A wide range of consumer data is now available as input for generating automated brand content. These perceptions and attitudes toward data collection practices and use are discussed at length elsewhere in this volume of the *Journal of Advertising* (Helberger et al. 2020). For the purposes of understanding consumer data's role in optimizing brand-generated content impact, this section first reviews key types of consumer data, then reviews empirical studies that highlight the consumer data element's role as moderators that could change or strengthen the direction of the impact of automated brand-generated content.

The data used to optimize and automate brand-generated content is usually user-centric in that it describes the (prospective) consumer. Sometimes—although unfortunately rarely—such consumer data are gathered with explicit consent, meaning that people volunteer their information willingly and truthfully because they believe it will be used to provide them with better options, greater convenience, or some other benefits, like access to free content (Estrada-Jiménez et al. 2017). An example is surveying people about their preferences to refine the set of recommendations provided to them (Sun and Zhang 2018). Besides opt-ins, consumer data can also be derived from third parties (Malthouse, Maslowska, and Franks 2018) and are increasingly accessed via data management platforms (DMPs; Elmeleegy et al. 2013). Digitization enables the collection of many types of online consumer data (e.g., Boerman, Kruikemeier, and Zuiderveen Borgesius 2017) that can be used as inputs for automated brand-generated content.

Consumer data can include demographic information (e.g., age, gender, education level, income, geography, marital status) and, through the adoption of social networking services, pictures and/or videos, interests, and relationships (Karahasanović et al. 2009) and, through the use of mobile devices, location-based information. In addition, more nuanced psychographic information to understand stated preferences and observed choices are also used in psychographic marketing. Such psychological characteristics and traits convey the consumer's personality (e.g., introversion or extraversion) and values (e.g., concerns about the environment). Moreover, consumer data can also relate to online media consumption, browsing, and shopping, while surveillance-enabling devices such as smart speakers, virtual assistants, and health/fitness trackers facilitate even more pervasive data collection. Third-party data can include audience analysis by Facebook and/or Google (Busch 2016).

There is tension between what data collection is technologically possible, what data collection is being used and practiced, and what data are examined in academic research for automated brand-generated content. Whereas digitization allows for the collection of many types of online consumer data that can be used as input for automated content, academic research has a strong focus on behavioral advertising, which relies primarily on inputs from online behavioral data (e.g., browsing behavior; e.g., Liu-Thompkins 2019). Other types of data are largely disregarded in examining the impact of automated brand-generated content. To our knowledge only one study explored the impact of personality-tailored social media ads (Zarouali et al. 2020). At the same time, academic research clearly demonstrates that this narrow focus on behavioral trace data is insufficient to understand the impact of automated brand-generated content. Some decades ago, it was taken for granted that with advances in information technology we would finally focus on actual behavior to assess the value of marketing communication (e.g., Schultz 1998), yet academic research clearly shows the importance of consumer attitudes and perceptions. So far literature has generally neglected these variables when examining impact.

While the practice of brand-generated content is becoming more common, consumer perceptions and concerns for data collection as input for automated content may become more important. This aspect is exemplified by a recent Pew Internet study (Auxier et al. 2019). This study of Americans reported that the majority are aware of and frequently have seen ads that are based on their personal data, and, although respondents report that these ads accurately reflect their actual interests and characteristics, they also report concern about the amount of personal data being collected by advertisers and the companies from which they make purchases. Also, 81% say that they have little or no control over the personal data collected by companies and that the risks of such data collection outweigh the benefits. Thus, while the practice of using consumer data for optimized content is growing, so too are consumers' concerns. Literature indeed provides empirical support for the notion that successful brand-generated content depends on a wide range of consumer perceptions, attitudes, and characteristics.

A helpful starting point for understanding consumer-related attitudes and characteristics in relation to automated brand-generated content is research on online behavior advertising (OBA). OBA is defined as "the practice of monitoring people's online behavior and using the collected information to show people individually targeted advertisements" (Boerman, Kruikemeier, and Zuiderveen Borgesius 2017, p. 364). A recent literature review of OBA (Boerman, Kruikemeier, and Zuiderveen Borgesius 2017) identified a wide range of consumer-level factors that affect consumer responses to ads, either directly or as mediating or moderating effects (for a discussion of moderating variables, see the Online Personalization section in Liu-Thompkins 2019).

In terms of perceptions, Boerman, Kruikemeier, and Zuiderveen Borgesius (2017) identified privacy concerns, attitudes induced by OBA, feelings of vulnerability, perceived usefulness of an ad, trust in an advertiser, feelings of intrusiveness, perceived personalization, ad skepticism, perceived risk, and perceived fairness of data used. At the consumer characteristics level, the authors detail, among other factors, privacy concerns (as a more stable consumer characteristic), desire for privacy, level of online experience, education, and age. For example, OBA is more effective for more vulnerable consumer audiences, such as children, who are less able to recognize the persuasive technique of data being used (see persuasion knowledge model; Friestad and Wright 1994), which subsequently causes stronger persuasive outcomes of personalized content (e.g., Van Reijmersdal et al. 2017). Literature illustrates the impact of these factors on advertising effectiveness, such as click-through intention and behavior, purchase intention and behavior, brand recall, and perceived ad relevance. The authors also illustrate how consumer-level factors can explain OBA acceptance and advertising avoidance. In a similar vein, such variables might influence how consumers respond to automated brand-generated content.

One direct impact of privacy concerns on automated brand-generated content is the potential decrease in available consumer data from some populations. As privacy concerns abound (Buchanan et al. 2007), consumers are motivated to turn optimization off (Strycharz et al. 2019b) and seek novel means of keeping their personal data from getting into the hands of brands—in some cases taking relatively simple steps to delete cookies showing their web-browsing history; in other instances even going out of their way to misrepresent themselves and throw advertisers off their scent, so to speak (Boerman, Kruikemeier, and Zuiderveen Borgesius 2017). Consumers have developed several strategies for controlling the contexts in which they see ads and/or limiting overexposure. First, ad-blocking tools have grown in popularity as a way for consumers to avoid unwanted advertising (e.g., Boerman, Kruikemeier, and Zuiderveen Borgesius 2017). A report by eMarketer (2019) shows that roughly one-quarter of Internet users relied on ad-blocking tools as of 2019. Another study by the Spiegel Research Center found that consumers who used ad-blocking software were more likely to keep subscriptions to news publications, presumably because they were not as put off by the ads therein (Jacob 2019). Privacy concerns are positively associated with such behaviors, including ad avoidance (Baek and Morimoto 2012; Jung 2017) and privacy protection behaviors in relation to OBA (e.g., blocking pop-ups, removing cookies; Smit, van Noort, and Voorveld 2014).

Furthermore, consumers often have the option to pay for ad-free subscription services to access the same desired content that would otherwise be overlaid with ads in some fashion. Of course, consumers seemingly have a choice to simply avoid using a service if they do not appreciate the way their data are used or ads are targeted to them, as has been widely studied when it comes to "quitting" Facebook (Stieger et al. 2013). At the same time, many consumers believe surveillance is inevitable and they will be unable to make data collection stop (Strycharz et al. 2019c). Such feelings of resignation might turn consumers to stop wanting to receive personalized content (Turow, Hennessy, and Draper 2015). Such "chilling" behaviors on the consumers' part are associated with online privacy concerns, as confirmed by a meta-analysis (Baruh, Secinti, and Cemalcilar 2017). This evidence for chilling behaviors (and privacy concerns) is mainly provided by research on advertising and personalized recommendations. But with the increased adoption of surveillance-enabling devices and tools, we feel comfortable arguing that consumers develop such behavioral strategies to brand-generated content in the broad sense. Consumer characteristics, such as gender and age, may increase such chilling behaviors, as young women are more concerned about their privacy (Hoy and Milne 2010).

Consumer expectations with regard to transparency of data collection are also important in shaping consumer receptiveness to personalized content. However, evaluating the effect of such perception on automated brand-generated content impact reveals a paradoxical effect. On one hand, Awad and Krishnan (2006) found that consumers who reported a greater desire for information transparency were less willing to be profiled by advertisers. On the other hand, Aguirre et al. (2015) found that while consumers initially reacted negatively to notes on websites that inform users about data collection, they showed appreciation for the transparency over time, demonstrated by increased click-through rates (CTRs). Thus, research is so far inconclusive about how transparency influences impact in the long run.

Another gap in literature regarding the direction of the effect of automated brand-generated content arises when aiming to understand the unique impact of consumer perceptions of specific types of personal data. In particular, while law and regulations are clear about what kind of data are considered personal, consumers do not perceive all personal data used for optimization as equally personal; some types of data are perceived as more sensitive (e.g., see Table 1 in Walrave et al. 2018). Depending on the privacy sensitivity of the data used for optimization, then, consumers may respond differently to optimized content. This is also the reason why some scholars argue that, when examining impact, consumer perceptions with regard to optimized content should be the starting point (e.g., De Keyzer, Dens, and de Pelsmacker 2015), rather than the actual level of personalization in the content.

In a similar vein, consumers might hold different perceptions toward the collection of data through different types of data sources (e.g., web, social media, mobile apps). While people welcome surveillance-enabling devices such as smart speakers, virtual assistants, and health/fitness trackers into their homes and lives for the benefits they offer, popular press reports a corresponding increase in concerns by consumers that they may lose autonomy over their personal data or that companies may misuse their data (e.g., BBC News 2019). Empirical studies on the willingness to share personal data also provide further evidence that consumers hold different perceptions toward different types of data and that these perceptions have consequences for automated brand messages as they affect likelihood to share different types of information (Walrave et al. 2018; Phelps, Nowak, and Ferrell 2000; Leon et al. 2013).

Because the automation of brand-generated content takes advantage of a wide range of consumer-centric data (Zuiderveen Borgesius 2015), it is important to consider the direction and strength of impact of consumer perceptions toward these different types of data and data sources when optimizing brand messages. Newer types of data should also be considered in this respect. While a range of research has demonstrated that data-related variables moderate the strength or direction of the impact of automated brand-generated content, research on newer types of data remains in its infancy. Taken together, this suggests that different types of consumer data must be considered in the ABC model.

Implications for the ABC Model

In sum, one challenge for automated brand-generated content is that consumers' privacy-related attitudes and perceptions, including expectations of transparency, should play a key role in determining the extent to which personal data should be used for brand-generated content that is optimized to the individual consumer. We propose that different types of consumer data should be considered in automating brand-generated content. This includes data about consumer attitudes and perceptions, demographics, behaviors, and psychographics; each of these types of data can be either shared by the consumer or inferred in some way. Such data can be derived from zero-, first-, second-, and third-party data (Yun et al. 2020). Furthermore, attitudes to new data sources and data collection practices should be considered.

Brand Data

What is the role of brands in automated brand-generated content? As personalized advertising content generation is primarily consumer based, rather than brand characteristics focused, what remains of the brand? In fact, one model proposed for personalization by Vesanen and Raulas (2006) considers only consumer data and disregards brand data. In line with Yun and colleagues (2020) we argue that brand data should be considered as inputs for optimizing brand-generated content. More specifically, we address three brand-related characteristics: brand identity (considering both coherency and centrality of values to brand identity), brand trust, and brand relationship quality (BRQ).

A brand is the way an organization is perceived by those who experience it, often conceptualized as brand identity. Brand identity refers to a distinct set of brand associations that represents what the brand stands for in consumers' minds (Keller 2012). It is expected that brand managers ought to develop a clear and consistent identity so that they can serve as stable references for consumers (Aaker 1996). O'Shaughnessy (1987) suggested that brand identity is a necessary condition for sustaining a buyer's trust. Indeed, a coherent brand identity was found to be positively associated with perceived brand trust and value (He, Li, and Harris 2012; Shirazi, Lorestani, and Mazidi 2013). Furthermore, in relation to a set of brands, or a brand portfolio, it was also demonstrated that it is important for (sub)brands to share a common logic as perceived by the consumer, as this increases trust. More specifically, Nguyen, Zhang, and Calantone (2018) found that brand portfolio coherence (i.e., in terms of communicating a consistent design, personality, and status) is associated with increased trust.

A coherent brand identity may, therefore, be at odds with brand-generated content that is optimized toward each individual consumer. The tension involves, on one hand, striving for unity of brand representation in advertising across consumers and, on the other hand, aiming to convey a message uniquely suited to each consumer. Furthermore, as social value plays a growing role in brand identity (Vargo and Lusch 2014), brands may be more susceptible to the negative impact of consumer data–based content creation. An established body of literature has found that more trusted brands (e.g., Bleier and Eisenbeiss 2015) as well as brands with higher BRQ levels (Smith, Chen, and Yang 2008) have benefited more from automated brand-generated content. As a research agenda, we propose to explore the impact of brand elements, including coherence of brand identity and centrality of values to brand identity, on the impact of automated brand-generated content.

As contents of automated brand-generated content may differ from completely optimized to the consumer to fully brand generic, brands may create a different world for each and every consumer. This means that the way the brand is represented may vary markedly from one consumer to the next. This variability is problematic for the brand for at least four reasons. First, it may dilute brand identity, which is detrimental to the long-term strength of the brand. Some practitioners recognize and attempt to overcome this problem in their customer communications with so-called rescue boxes (Strycharz et al. 2019a). This is a space in which impersonalized and thus generic content is shown to avoid every consumer ending up in his or her own bubble and having a completely different experience with the brand.

Second, erosion of brand identity may jeopardize consumer trust and thereby the ongoing ability to optimize content, because consumers are less willing to share personal information with less trusted brands (Wottrich, Verlegh, and Smit 2017). Also, Smith, Chang, and Jang (2008) found that BRQ is positively associated with willingness to share personal information and reduces fears of inadequate privacy protection. Thus, as automated brand-generated content aims to tailor content to an individual's characteristics, brand identity may be diluted, in turn diminishing the effectiveness of automated content.

Third, as consumers and society at large are becoming more concerned with corporate practices, more brands have put forward their core values, building a value-based foundation for their relationship with consumers. For such brands, it is especially important to ensure that core values are not ignored or violated by automated content tailored to the consumer. The established relationship between coherent brand identity and brand trust (He, Li, and Harris 2012; Shirazi, Lorestani, and Mazidi 2013) may imply that violations of either have more damaging consequences for value-focused brands.

Fourth, a brand with less central automated brand-generated content may have more limited success, as trust in the brand is crucial for a success. For example, Bleier and Eisenbeiss (2015) showed that level of trust in a retailer increases the effect of personalized advertising banners, in terms of ad impressions and CTRs. For more trusted retailers, personalization was perceived by consumers as useful; for less trusted brands, personalization elicited reactance and privacy concerns. Thus, less trusted brands seem to benefit from using lower levels of personalization. Also, Wottrich, Verlegh, and Smit (2017) showed that consumers are more inclined to share personal information, such as name, sex, age, e-mail address, postal code, and telephone number, with more trusted brands. Furthermore, Smith, Chen, and Yang (2008) suggest that "some brands possess certain traits that make relationships with them—as friends or as lovers—easier" (p. 632). Considering their finding that the quality of the relationship with the brand is positively associated with willingness to share personal data and reduce privacy concerns, brand personas or traits should be a key consideration in the optimization of content and when balancing consumer and brand data.

Research that is focused not so much on a brand but rather on the industry or the context in which it operates (e.g., commercial versus nonprofit context) further stresses the importance of trust. A brand context was found to be associated with privacy preferences (see Acquisti, Brandimarte, and Loewenstein 2015; Nissenbaum 2004). Trust differences between contexts influence the balance between perceived benefits and costs, as well as between processes that enhance and hamper persuasion.

Implications for the ABC Model

Although automated brand-generated content might have the potential to dilute brand value, its impact can be increased by trust in the brand and the media in which the content is delivered, and it can also be increased for generally strong brands. Thus, the challenge is to integrate such brand-related variables in the process of automated brand-generated content and to balance them with consumer data in the content optimization process. Three brand-related characteristics, then, should be added as inputs to the model: brand identity (considering both coherency and centrality of values to brand identity), brand trust, and BRQ.

Impact

A broader discussion of measuring impact of computational advertising and its related challenges is provided in length by Yun and colleagues (2020). For the purposes of understanding impact as an element in the ABC model, this section focuses on impact in terms of responses to automated brand-generated content.

One-on-one optimization in brand–consumer interactions has been practiced to grow near-term business goals (e.g., Strycharz et al. 2019a). For automated brand-generated content this means there is a focus on consumers' immediate behavioral responses to content, such as clicks, likes, comments, views, completes, and opens. Digital environments allow for real-time large-scale experiments to examine these responses, also known as A/B testing, in which the impact (or performance) of multiple impressions or variations in content can be tested in real time on a subset of (prospective) consumers and customers. Such possibilities might drive the short-term focus and increase the weight of direct responses to content.

In academic studies, the impact of automated brand-generated content has also mainly been researched with a focus on short-term consumer responses. Studies primarily focused on short-term consumer attitudinal and behavioral responses (e.g., ad clicks, opens, likes, sentiment in comments) to content that is optimized to the individual consumer or segments of consumers (e.g., Bol et al. 2018; Strycharz et al. 2019a). Less research is focused on what the content does for the brand (e.g., brand perceptions, including brand trust), especially in the long run. Moreover, with a few exceptions, there is a strong emphasis in this research domain on experimental designs and self-report measures (e.g., Bol et al. 2018) related to personalized content.

Studies on automated brand-generated content (mainly being examined as recommended content and behavioral advertising) explore how such content not only enables persuasive outcomes but also has detrimental effects. In fact, many studies highlight these countervailing effects of automated brand-generated content, meaning that its impact is not straightforward: Findings are contradictory (i.e., show both enhancing and hampering processes for persuasion) and conditional (i.e., on the consumer, brand, the data used, and the mode of delivery). First, studies demonstrate that it is beneficial for consumers (e.g., to receive better offers or preference matches; Vesanen and Raulas 2006) and that it is able to enhance persuasion (e.g., through increasing relevance, attention, and elaboration; Tam and Ho 2006), yet at the same time it may hamper persuasion (e.g., through raising privacy concerns and perceptions of creepiness; Awad and Krishnan 2006). That such personalization has positive and negative outcomes at the same time is sometimes referred to as the *personalization paradox* (Lee and Cranage 2011). One prevailing belief is that the sum of consumer-perceived benefits and costs determines the persuasiveness of content that is optimized to the consumer. This is explained in the privacy-calculus theory (Dinev and Hart 2006). In addition, scholars stress that so-called chilling effects (Strycharz et al. 2019c) and information or cognitive overload are detrimental for persuasion because it is impossible for consumers to pay attention to the stream of targeted and personalized messages that confront them 24/7 via an enormous amount of media.

Second, research focuses on multiple moderating variables that could change or strengthen the direction of the impact of automated brand-generated content. Such variables are related to the consumer and the brand or rather the industry, context, or sector in which it operates, and related to the mode of delivery. Explanations for such conditional effects center around the idea that privacy and privacy preferences are context dependent (Acquisti, Brandimarte, and Loewenstein 2015; Nissenbaum 2004) and differ among people (e.g., Smit, van Noort, and Voorveld 2014). Such differences between contexts and individuals influence the balance between perceived benefits and costs, between processes that enhance and hamper persuasion. For example, with regard to mode of delivery, it is argued and demonstrated that consumers do not equally trust media with their data for targeting purposes. Differences occur between offline media (e.g., Yu and Cude 2009) and online media (e.g., Smit, van Noort, and Voorveld 2014) and also between chatbots and websites (Ischen et al. 2019). Brands advertising in more trusted online media are perceived as more trustworthy and their ads are more effective. Thus, trust in the online media brand is transferred to the advertising brand (Mediabrands, Sanoma, and Alpha One 2018). This implies that the persuasiveness of optimized content might differ between brands, consumers, and media contexts. In sum, findings clearly show that automated brand-generated content is not equally effective for everyone. Impact varies for each brand and the industry or sector in which the brand is operating (e.g., health, nonprofit, profit, journalism), as well as for all types of data that can be used. Finally, impact differs across delivery modes.

Implications for the ABC Model

For a sustainable automated brand-generated content process, we argue, impact should be evaluated in terms of both short-term impact and long-term impact, including responses toward the brand and not just the content, and including responses toward the phenomenon of automated content in general. Impact should feed back into brand data and into consumer data, making it not just an outcome but also as an input. Another implication is that modes of delivery should be part of the ABC model: Optimized brand-generated content can be delivered to the consumer via manifold media, but a framework for this is lacking.

The ABC Model: A Research Agenda

How can this phenomenon be examined, taking into account current practices and academic findings? Based on the discussion of the key elements of the ABC model, three major considerations arise that inform the ABC process: the intrinsic importance of the brand, the impact goal, and consumer attitudes. Alongside the overall success of automated brand-generated content, then, lie challenges. Better understanding of consumer-level attitudes toward automated brand-generated content, including privacy concerns, brand characteristics, and the unique nature of different data types, are all critical for the optimization of automated brand-generated content. Based on the discussion of the key elements of the ABC model, these research themes, related research questions and propositions (see supplemental online appendix) can be derived and fuel the ABC research model (see Figure 2). We organize this research agenda by first addressing research related to automated brand-generated content and then discuss the agenda for data inputs (i.e., consumer and brand data) and for impact.

Automated Brand-Generated Content

A most pressing research question related to automated brand-generated content: How should one determine the weight between different types of consumer data and between brand and consumer data in the optimization process? As we argued, consumer attitudes and perceptions might be more important than other types of consumer data in this process. Therefore, an important question is whether indeed consumer attitudes and brand data determine the weight that should be given to either consumer or brand data in the process to reach the desired impact, and whether behavioral and psychographic consumer data can be considered less informative in determining this weight. For example, is brand trust more important than consumer privacy concerns for long-term engagement with automated brand-generated content?

A second theme is related to content formats. In our conceptualization of automated brand-generated content, we stress that content is elastic and is much broader than advertising. Thus far, academic research has examined different types of content but focuses mainly on online behavioral advertising in the context of online display advertising and social media advertising. Considering the shift in brand-generated content, automated one-to-one communication—for example, via conversational agents (i.e., chatbots, home assistants)—is an emerging research field (SWOCC 2019). While current research frameworks focus more on automated advertising copy (e.g., display and social media ads), future research should address content that is more dynamic and part of the brand–consumer conversation. Voice, virtual, and augmented content should also be considered in future research.

Consumer Data

Within the research theme of consumer data, it is crucial to extend empirical research to content that is based on consumer data other than behavioral trace data. The possibilities for data collection will increase at an unprecedented pace, partly due to technological developments in the field of computing and the further integration of digital devices into the daily lives of consumers. For example, the growing popularity of conversational interfaces, such as chatbots and voice-first devices, can potentially provide additional sources of data to consider (Sotolongo and Copulsky 2018). It will be difficult to keep up with these developments in empirical research, yet it is crucial to increase our understanding of automated brand-generated content. The challenge is to include consumers' privacy-related attitudes and perceptions, including expectations of transparency in this empirical research, as consumers hold different opinions with regard to data types and data collection sources. To advance the research agenda in this direction, we built upon the existing literature on consumer data collection (e.g., Phelps, Nowak, and Ferrell 2000; Leon et al. 2013) and the role of consumer privacy concerns in response to personalized messaging.

More specifically, we propose a research agenda to investigate the impact of consumer data that are either shared (i.e., disclosed by the consumer) or can be observed or inferred. First are attitudes and perceptions, including privacy-related attitudes, attitudes toward data collection and use (e.g., perceived control, sense of intrusiveness), attitudes toward advertising (e.g., trust in advertisers, ad skepticism, ad irritation), and expectations toward transparency. Second are data collected about and extrapolated from users' activities online, including demographic data (i.e., who is the consumer), behavioral data (i.e., how does the consumer behave; e.g., browsing information from the brand website and the web in general, media consumption, and purchasing history), psychographic data (i.e., what is the personality of the consumer; e.g., based on text analyses of social media content posted by consumers or based on the voice used in conversations with voice-based assistants). Future research should try to determine how impactful automated brand-generated content is based on these types of consumer data.

Another important venue for research within this theme is the relative importance of consumer data. In the area of personalized advertising, scholars argue that, when examining impact, consumer perceptions with regard to optimized content should be the starting point (e.g., De Keyzer, Dens, and de Pelsmacker 2015) rather than the actual level of personalization in the content. Also, consumers might hold different perceptions toward the privacy sensitivity of specific data (e.g., demographic versus psychographic data) and the collection of data through different types of data sources (e.g., web, social media, mobile apps). Thus, although the proposed ABC research model visualizes all kinds of consumer data (i.e., demographic, behavioral, psychographic, attitudinal) in one box, research clearly shows that different consumer data should be treated differently in the automation process. Future research should answer the question whether perceptual and attitudinal data are more important in determining the impact of automated brand-generated content than other types of consumer data.

Furthermore, because of the paradoxical effects of transparency of data collection practices, future research should delve into this issue. It is possible that a longitudinal approach looking at the relationship between expectation for transparency and willingness to share personal information may provide tools for addressing this transparency paradox. Other venues for future research on transparency are provided by Helberger et al. (2020).

Brand Data

Brand data research is still in its infancy. Based on our literature review, we suggest at least the following brand characteristics that should be considered in the ABC model: coherence of brand identity, centrality of values to brand identity, brand trust, and BRQ. Research in the area of these brand characteristics is scarce (e.g., mainly related to online personalized advertising) and inconclusive but indicates that they may influence the impact of automated content. Future research should therefore answer several questions, including the following: How impactful is automated brand-generated content for different levels of brand trust? Is automated brand-generated content more impactful when consumers experience a better relationship with the brand? What is the relative importance of brand characteristics in automated brand-generated content? Other challenging research questions consider the weight between consumer and brand data; these are discussed next.

Impact

Related to the impact theme, future research should consider long-term impact and impact of content on the brand. More specifically, research should investigate both short-term responses to content, such as online behavior (e.g., clicks, time spent on site, time looked at an ad via eye tracking), attitudes toward a given message (e.g., perceived usefulness), and immediate buying (intentions) of a product; as well as long-term impact, which includes over-time buying intention of a brand, attitudes toward a brand, and attitudes toward automated brand-generated content in general. As the output of the model is also considered as input for brand and consumer data, future research should also investigate how these outcomes or impact measures feed back into brand data (e.g., how it informs the brand value) and consumer data (e.g., how it informs consumer data such as interests). Moreover, it should be investigated how short- and long-term effects are related; this is a challenge in itself (see for a discussion on this challenge, see Yun et al. 2020).

Another important theme for future research is the mode of delivery. A framework for this is lacking, while technological developments may create an infinite set of channels and delivery modes, and research on the impact of automated content clearly shows that delivery modes change the magnitude and direction of the impact. It should be investigated to what extent levels of trust differ between different media and modes of delivery and how this influences short- and long-term effects.

External factors

In determining the weight between consumer and brand data for automated brand-generated content, at least two other factors should be considered: stages in the customer journey and contexts. We argue that early on in the customer journey, when consumers are first confronted with the brand, it is important to get familiar with the brand and its values; and that when a strong brand identity and relation are built, messages can be tailored more toward consumption moments. This means that early on in the customer journey the emphasis given to brand (versus consumer) data is more important. Another important venue for research is the moderating impact of contexts (e.g., commercial versus nonprofit or health versus e-commerce). As research indicates that trust differs between different contexts, it is important to examine whether the balance between brand and consumer data should differ between such contexts. Possibly the automation of brand-generated content based on several consumer data types is less accepted and trusted in some contexts, which then requires relatively more weight for brand (as opposed to consumer) data for impactful content.

Finally, for sustainable automated brand-generated content, we consider that external data, such as information about societal and economic trends, public events, and cultural and social norms, influence both the weight that should be given to different types of consumer data and consumer versus brand data and the impact of automated content. For example, optimizing toward the individual consumer, while not taking into account important societal values (i.e., toward emerging political or environmental issues) and events, might damage the relevance of optimized content. Thus, the economic, societal, cultural and environmental context should never be neglected in the process of creating and delivering brand-generated content. Future research could answer the questions how such data should inform the automation process. Finally, we recognize that other factors at the more macro level, including regulations and legislations, are significant as well, although, while usually constant within countries or even between countries (e.g., the European Union), these might be related more to what kind of consumer data is collected and used than to determining the balance between consumer and brand data

Implications for Practitioners

Although the ABC model might be useful for more impactful and sustainable automated brand-generated content, there are several practical challenges for adopting this model. First, in the industry there is a strong emphasis on adapting content to digital trace data or behavioral data (e.g., Yang et al. 2017), making it difficult to cater content to other consumer-related data such as motivations, beliefs, and attitudes behind these behaviors. Data-driven organizations may have an advantage in adopting the ABC model because access to these data, for example, via data management platforms, is crucial. Other challenging factors are at the organizational level. Organizational frameworks, structures (e.g., in which brands, innovations, and digital marketing are managed from separate departments), and processes can be enemies of progress, making it difficult to manage the brand as part of automated brand-generated content. One important question in this respect: How should creativity be organized? Because of the natural tension between automation and creativity, it might be necessary to integrate tools for automated content generation in organizational and creative processes in such a way that they advance computer-*facilitated* creativity instead of computer-*generated* creativity. In this respect Lubart (2005) discussed four different futures for computers in creativity: the computer as (1) a nanny (e.g., provide room for creativity by taking care of routine tasks), (2) a pen pal (e.g., facilitating exchange of ideas between creatives), (3) a coach (e.g., tutorials to stimulate cognitive processes such as free association), and (4) a colleague (e.g., an iterative process between a human and computer to generate ideas and content).

Summary and Conclusion

We have illustrated that technological developments, mainly related to algorithms and computational power, changed how brands create and deliver their messages, something that becomes evident in our proposed (ABC) model. This articke's contribution is threefold 1) we discussed how brand-generated content emerges in a communications environment increasingly influenced by computational methods, 2) we extracted key variables that determine the impact of automated brand-generated content on outcomes of interest, and 3) we identified empirical gaps in understanding the relationship between inputs and desired impacts (both short- and long-term) in order to propose a research agenda for future work. The ABC model underlies our discussion of the process of the automation and optimization of brand-generated content in this article. The model illustrates that automated brand-generated content involves an iterative process in which both consumer and brand data fuel the optimization of such content, and that both long- and short-term impact on the consumer and the brand should feed back into the process. Based on a detailed discussion of current practices and academic findings for each of the key elements in the model, we derived implications for the ABC research model, research themes, research questions, and propositions.

Researchers are encouraged to use this model to advance an understanding of automated brand-generated content in a computational era. The future research agenda (see supplemental online appendix) provides guidance in this, but we recognize that there is an evolving path forward. First, technological developments will provide new consumer data and brand data sources to leverage as inputs, as well as better information about measuring impact. Second, a next step would be automation of the model itself. Automation of the testing of the models' functions may further improve the model. All together future research may provide insights in whether the proposed ABC model is future proof and elastic enough to address new and important elements in the advertising landscape that emerge in response to technological advancements.

At the same time, we hope to inspire practitioners in their thinking about how brands are connecting and engaging with consumers in ways that benefit them and consumers in the near and longer term. Our hope is to remind them of the consequences of so-called Faustian bargains, sacrificing long-term results for shorter-term impact. Without this insight, the risks could be great that consumers will just tune out those brands that, colloquially, just don't get it.

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