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From Purchasing Exposure to Fostering Engagement: Brand–Consumer Experiences in the Emerging Computational Advertising Landscape

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ABSTRACT

Over the past 40 years, we have witnessed seismic shifts in advertising planning and buying processes. Due in no small part to the emergence of digital media, consumer choices have mushroomed, while advertisers understand much more about target audiences. Advertising activities have been drastically transformed by the possibilities that technology creates for targeting and measurement, automation of activities via programmatic advertising, and an overall computational approach in which algorithmic, data-driven decisions dominate. In this era, what does it mean to “do media planning” and to do it well? The present article argues for planning decisions to move away from simply purchasing exposure to instead focusing on fostering engagement through meaningful and sustained interactions with consumers. It provides an overview of the digital ecosystem that makes computational advertising possible, updates the notion of consumer engagement for this context, and reviews how measurement becomes more central to media planning decisions. Ethical and normative considerations and computational advertising as an adaptive learning system are discussed as crosscutting issues, followed by a proposed research agenda.

If we rode in our time machines back to the early 1980s, we would find a world in which commissioned advertising representatives worked hard to convince media-buying agencies that their particular media delivered the audiences that brands wanted to reach. Significant investments were made in market research to demonstrate how audiences delivered by the media engaged with various product categories. Elaborate rituals accompanied the buying process, including the collection of television diaries from millions of U.S. households as part of the annual “sweeps” and the unveiling of fall television schedules in conjunction with broadcast “upfronts.” Meanwhile, advertising representatives and media buyers scrambled to negotiate the best prices for the available inventory.

Advertisers back then were buying exposure to the audiences that they thought mattered, with some attention to context: the right magazine, television show, and location for site-based advertising. The planning challenge was trading off reach and frequency (i.e., the total size of the target audience and the number of times when this audience is exposed to

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the ad message) with precision (i.e., how much of the audience truly represented the advertiser’s desired targets). The relevant metric was the cost per thousand (CPM), a convenient way to communicate the expense associated with reaching 1,000 potential customers. The stakes were significant, with audiences of more than 20 million households tuning into popular 1980s’ television series like Dallas or Dynasty.

On the back end, the challenges were to show that

- the advertisements actually ran (hence, the origin of “tear sheets,” pages cut from a publication to prove that an ad was published);
- the audience size and composition were as promised; and
- the audiences saw and remembered the ads, on an unprompted and prompted basis.

However, except for direct response advertising, establishing a linkage between exposure and purchases was generally a leap of faith.

Over the past 40 years, we have witnessed seismic shifts in the advertising ecosystem and the advertising planning and buying processes. Due in no small part to the increasing prevalence of digital media, customer choices have mushroomed, while advertisers understand far more about the characteristics and habits of their target audiences. The locus of control has shifted to consumers, who choose which content to consume and when and where to consume it. They choose whether to skip ads or not. They decide if, when, and where to initiate conversations with brands or other consumers. Many trade-offs between reach/frequency and precision have been at least partially broken (e.g., advertisers can display their ads to more targeted audiences), and much of the media planning process has shifted from negotiated to programmatic purchases. Insights about audience targeting are based on data about user preferences and behaviors extracted from their digital footprints. Armed with these insights, advertisers use data management platforms to construct their ideal audiences. Sellers use supply-side platforms to manage their inventories while advertising networks aggregate inventory from multiple publishers and match it to the demand from advertisers (Busch 2016; Qin and Jiang 2019). In short, we have moved to an era of computational advertising focused on placing “the best ad in the best context before the right customer” (Essex 2009, 16), with stronger capabilities to track user activity—from exposure to action and conversion—supported by increasing opportunities for personalization.

In this computational advertising era, what does it mean to “do media planning” and to do it well? Who are the new actors that influence the media planning process? What are the relevant measures when the focus of media planning becomes fostering engagement? What considerations do professionals face when choosing channels for message delivery and what media strategies to pursue when planning interactions with their target audience? What are the practical and theoretical implications of the emergence of computational advertising?

Against this background, we review fundamental changes occurring in the field of media planning and buying. We seek to identify key challenges for media planning professionals and advertising researchers within a computational advertising paradigm. In this article, we approach computational advertising with broad strokes. We focus on how online behavioral advertising (Boerman, Kruikemeier, and Zuiderven Borgesius 2017) makes use of digital trace data to show increasingly targeted advertising. This is often achieved via programmatic advertising processes “through which media sellers and buyers align organizational processes with automation technology in support of ongoing, channel-agnostic customer engagement” (Winterberry Group 2013, p. 3).

We also explore the broader implications of the computational turn, including the emergence of a digital ecosystem and of new actors that influence the brand–consumer relationship. This computational turn requires, we argue, moving from purchasing exposure toward fostering engagement through meaningful and sustainable consumer interactions.

This article is organized as follows: We begin with an overview of the digital ecosystem that makes computational advertising possible. We then discuss the notion of consumer engagement and the implications of different aspects of computational advertising. Next, we discuss measurement as a central aspect of this ecosystem and implications of computational advertising for interaction planning and, consequently, fostering engagement. Finally, we discuss crosscutting issues and propose a research agenda for computational advertising.

The Digital Ecosystem

The move toward digital environments has fundamentally transformed the media landscape and, consequently, what it means to do media planning. The consumer experience has shifted toward media consumption across multiple screens and devices (Kumar and Gupta 2016), with increasingly blurred boundaries between the online and offline worlds. Social media have brought fundamental changes to “the way we communicate, collaborate, consume and create” (Aral, Dellarocas, and Godes 2013, p. 4), including and especially in how consumers
interact with brands (Kaplan and Haenlein 2010; Mangold and Faulds 2009).

For advertisers, these changes mean, at a minimum, that ever-growing sets of options are added to the portfolio, reaching a point at which professionals struggle to decide which options or combinations to use (Keller 2016). Advertising activities have been drastically transformed by new possibilities for targeting and measurement (Kumar and Gupta 2016), automation of activities via programmatic advertising (Winterberry Group 2013), and an overall computational turn in which algorithmic, data-driven decisions become prevalent. There has also been a shift between traditional and online advertising (Kumar and Gupta 2016) and, importantly, in the balance of power between brands, media producers, consumers, and especially the digital platforms that shape this contemporary media landscape (Labrecque et al. 2013).

A new digital ecosystem has emerged, which can be defined as “business environments shaped by a network of interdependencies generated through digital technologies” (Kopalle, Kumar, and Subramaniam 2020, p. 115, citing Subramaniam, Iyer, and Venkatraman 2019). This ecosystem is a complex matrix composed of large technology platforms (e.g., Facebook, Google, Apple, Amazon, Microsoft) and smaller players, across what can be called the “social quantification sector” (Couldry and Mejias 2019). They include “hardware, software, platforms, data analytics, data brokerage firms, and even spammers” (Mejias and Couldry 2019, p. 2). For advertising specifically, this ecosystem is directly visible in how publishers automatically interact with demand-side platforms from advertisers (Sinclair 2016), enabling programmatic and online behavioral advertising.

The rise of these new forms of advertising is just one aspect of this digital ecosystem. If advertising could once have been characterized as single-channel, one-way, brand-initiated, persuasive attempts in the traditional advertising ecosystem, it has now become a set of omni-channel, two-way (or multiple-way), user-generated (or multi-actor-generated) interactions throughout the consumer journey (Calder and Malthouse 2006; Rawson, Duncan, and Jones 2013; Schultz, Malthouse, and Pick 2012). As we argue throughout this article, the traditional notion of exposure-driven media planning needs to evolve toward the idea of interaction planning with consumers, with the aim of fostering engagement. Against this background, some aspects critical for interaction planning can be highlighted:

1. **Media convergence**—or the connections and interactions among previously unconnected media (Jenkins 2004; Smolin 2020); media convergence means that the boundaries between different media channels and between the advertising, technology, and media production sectors begin to blur (Kumar and Gupta 2016).

2. **Rise of social media** has given access not only to more insights about consumer preferences (Aral, Dellarocas, and Godes 2013) but also to new forms of interaction between consumers and brands, and among consumers about brands (Kaplan and Haenlein 2010; Mangold and Faulds 2009; Muntinga, Moorman, and Smit 2011). It also enables the emergence of new important actors, such as influencers.

3. **Datafication**—in other words, “the transformation of human life into data through processes of quantification, and the generation of different kinds of value from data” (Mejias and Couldry 2019, p. 3)—of more and more social processes is increasing. Previously nondigital activities—for example, looking at a map, talking to a friend, or even turning on lights—have all become part of the domain of (digital) data, in the format of GPS locators, Facebook posts, or commands to virtual assistants enabled in a smart home. These data points can be later (re)used for other purposes, including advertising decisions and brand interactions, potentially raising significant normative and ethical questions.

4. **Tracking everywhere**—Platforms allow customers to be followed across various websites and devices. Browsing sessions across multiple sites can be stitched together (Merriman and O’Connor 2006). This seamlessness, which is a powerful hook for consumers, provides a more comprehensive view of the consumers’ lives to advertisers (Mansour, Muthukrishnan, and Nisan 2012).

5. **The (potential for) personalization**—With increased tracking and datafication come increasing opportunities for personalization. Platforms have shown the power of personalization in driving up their own revenue (e.g., for e-commerce; Srilhari 2015). Consumers can be individually addressed based on their (digital) behavior using online behavioral advertising (Boerman, Kruikemeier, and Zuiderveen Borgesius 2017). While it is seen as an increasingly promising opportunity in the digital ecosystem (for an overview, especially in computer science, see the RecSys and SigIR conferences), it is also confronted...
with several challenges in practice (for an overview, see Strycharz et al. 2019).

6. The increasing relevance of artificial intelligence (AI) and related technologies—This ecosystem becomes a solid base for the development, implementation, and acceleration of AI and related technologies, either as part of its own constitution (e.g., with recommender systems playing a central role or the emergence of conversational agents) or as opportunities for advertisers (for an initial discussion, see Kietzmann, Paschen, and Treen 2018; Kaplan and Haenlein 2019).

The Structure of the Digital Ecosystem

The digital ecosystem includes the technological infrastructure that ensures an impression of an online advertisement is delivered to the device of a user, yet it encompasses a much larger set of processes: It changes the way consumers interact with brands and increases the ability to capture, quantify, and measure such engagement behaviors across different platforms and devices. We propose articulating these changes along the notions of emerging engagement arenas, assets, actors, and actions (Figure 1).

Arenas

The digital ecosystem multiplies the number of media channels or outlets that may be used as placement opportunities and fundamentally changes their nature, enabling two-way interactions where before there was largely one-way communication. Inspired by the concept of issue arenas (Luoma-Aho and Vos 2010; Vos, Schoemaker, and Luoma-Aho 2014), we suggest that advertisers should consider arenas, or places where consumers, brands, and other actors interact. In traditional advertising, if brands focus on buying space in somewhat static media products (e.g., ads in newspapers, television commercials) or physical spaces (e.g., out of home media), digitalization allows interactions to take place in online environments, and physical spaces that became digitized with the advent of the internet of things and smart devices.

While a full discussion of all potential engagement arenas is outside of our scope, we propose a broad distinction between (a) traditional (mostly offline) media; (b) the “open web” (or “the rest of the Internet,” as outlined by Deighton 2017), including online media more in general, outside of the walled gardens of social media platforms; (c) social media and messaging platforms; (d) smart and Internet of Things devices that digitize aspects of a consumer’s life that were previously offline (for an overview, see Petrovic 2017); and (e) digitalized public spaces, with beacons, sensors, and technology enabling new ways of interactions in offline spaces. It is important to highlight once more the notion of convergence: Interactions between brands, consumers and other actors happen within and across arenas.

Assets

Within each arena, different brand–consumer relationship assets are possible. The most traditional asset...
in advertising is paid media, or communications purchased by the brand to reach consumers. This takes the form of much of the (online) advertising spend but increasingly makes use of new digital opportunities—for example, paid partnerships with influencers (Domingues Aguiar and van Reijmersdal 2018), native advertising (Wojdynski 2016), and sponsored online reviews (Kim, Maslowska, and Tamaddoni 2019).

Brands also need to account for owned and earned media (for an overview, see Belden 2013; Corcoran 2009; Lovett and Staelin 2016). Owned media, communication touch points that the brand controls, now include the brand website or its social media profile, but also conversational agents in a private messaging platform (e.g., bots on Facebook Messenger) or virtual assistant integrations (e.g., Alexa Skills or Google Assistant Actions). Earned media in the digital ecosystem encompasses (free) media coverage and consumer-initiated brand actions (e.g., a favorable review on Yelp).

**Actors**

The main actors in traditional advertising ecosystems were media publishers and advertisers (and their agencies). Consumers were mostly relegated to the audience role, consuming media and being passively exposed to ads. The digital ecosystem requires a systematic reconceptualization of advertising and the role of its main actors (for an in-depth discussion, see Helberger et al. 2020). When it comes to the evolution of interaction planning decisions in this new ecosystem, it is important to highlight the role of three types of actors:

First, consumers are no longer just part of the larger passive *audiences* to be segmented and targeted; they become *actors*. Social media–empowered consumers share opinions and interact with others about brands via electronic word of mouth (eWOM; Hennig-Thurau et al. 2004; Hennig-Thurau et al. 2010) and posting reviews (Maslowska et al. 2019; Willemsen et al. 2011). Consumers also become important information brokers by helping bring brand-related information or viral advertising to new groups (Araujo, Neijens, and Vliegenthart 2017; Himelboim and Golan 2019). While WOM also exists in the nondigital world, and customer complaints are expressed to companies, consumer actions are now more visible and influence the same digital ecosystem where advertising and media publishers are located (for an in-depth discussion, see Liu-Thompson et al. 2020).

Second, *influencers* emerge as important actors who can facilitate or hinder interactions between brands and consumers. Research shows that some social media users have an extraordinary level of influence in information diffusion (Araujo, Neijens, and Vliegenthart 2017; Himelboim and Golan 2019; Subbian, Aggarwal, and Srivastava 2016). Influencer marketing (Domingues Aguiar and van Reijmersdal 2018; Jin, Muqaddam, and Ryu 2019), therefore, becomes crucial for advertisers. Identifying the right type of influencer (De Veirman, Cauberghe, and Hudders 2017) and understanding influencer marketing effects (Voorveld 2019, Kim and Srivastava 2007) represent key challenges in this area.

Third, *platforms* emerge as central, powerful actors, often in positions of dominance vis-à-vis other actors, including advertisers and media publishers. Google is responsible for much of the search activity, video consumption, and operating systems of smartphones used worldwide, provides many of the most widely used digital advertising solutions and web analytics suites, and is among the leaders in smart home devices. Facebook and its products, including Messenger, Instagram, and WhatsApp, are among the most popular social media and messaging services. It is also a leader in integrating user data from its platform to website activity through Facebook Pixel. Together, Google and Facebook are responsible for more than 60% of U.S. digital advertising spend (Perrin 2019).

Along with other large players (e.g., Alibaba, Amazon, IBM, Microsoft, Twitter, Tencent, and Weibo), these platforms give shape to the digital ecosystem itself. While they may often be associated with the social media or messaging arena, many of the services that power the “open Web” are enabled by platforms. This dominance points to a power shift, including in measurement and for interaction planning, as outlined in the section that follows.

**Actions**

The different actors—brands, content producers, consumers, influencers, and platforms—are active within this ecosystem and their actions influence the brand—consumer relationship. These actions may be brand, consumer, or other generated (Malthouse and Li 2017; Maslowska, Malthouse, and Collinger 2016). *Brand actions* in this setting encompass advertising, computational or otherwise, activities in owned media assets (e.g., newsletters) and earned media (e.g., press releases aiming at media coverage that will reach consumers). They also include web care (Van Noort and Willemsen 2012), and the deployment of conversational agents, such as chatbots on messaging platforms or brand websites or integrated into virtual assistant platforms.
Consumer actions in this ecosystem encompass dialogue, shopping, and use behaviors (Malthouse and Li 2017). Dialogue behaviors include consumer online brand-related activities, such as consuming, contributing to and creating brand-related content (Muntinga, Moorman, and Smit 2011), and acting as creators, metavoicers, or propagators (Liu-Thompkins et al. 2020). Shopping and use behaviors can be linked back to online purchases and the usage of (brand) products that generate digital trace data, which can serve as input for future interaction planning. When seen as an individual actor, a consumer is influenced by others-generated actions (Maslowska, Malthouse, and Collinger 2016). These “others” may be the (aggregated) actions of other consumers, but they may also be actions by other actors in this ecosystem.

A less explored set of actions is those of platforms. Although platforms often position themselves as neutral interfaces (Gillespie 2010; Helberger, Pierson, and Poell 2018; Van Dijck, Nieborg, and Poell 2019), their actions have widespread influence, pointing to a strong power shift. This influence is apparent, for example, in how changes in the Facebook algorithm affect content visibility (e.g., Bucher 2012), in content moderation decisions (Gillespie 2018), or, more broadly, in policies about acceptable content or advertising (e.g., political advertising, Kreiss and McGregor 2019).

The main changes from a traditional to a computational advertising framework within the digital ecosystem are summarized in Table 1.

| Table 1. From traditional advertising to the digital ecosystem. |
|-------------------|-------------------|-------------------|
| **Aspect** | **Traditional Advertising** | **Digital Ecosystem** |
| **Arenas** | Clearly delimited media channels (print, out of home, TV, radio) aimed at specific moments of consumption | Integrated digital touch points, multidevice media consumption and (co-)creation |
| **Assets** | Focus on paid media with carefully crafted media plans for campaigns | More and more social processes and physical spaces digitalized (datafication), Internet of Things |
| **Actors** | • Advertisers  
  • Selected set of content publishers  
  • Consumers as audiences | • Advertisers  
  • Broad range of content publishers (expanded by digitalization, Web 2.0, and social media)  
  • Consumers as empowered actors  
  • (Micro-)influencers  
  • Platforms |
| **Actions** | Advertising as brand-initiated, one-way communication actions | • Expanded set of brand-initiated actions (via paid, owned assets)  
  • Consumer-initiated actions  
  • Growing relevance of others’ actions, especially platforms |

**Consumer Engagement and Computational Advertising**

Consumer engagement is the lifeblood of the digital ecosystem. Media publishers and platforms rely, at least in part, on revenue generated by advertisers purchasing space. Ensuring mutually beneficial consumer–brand interactions with content and platforms is of the highest priority. A computational approach to interaction planning that identifies the best mix of consumer engagement opportunities for the brand and consumer benefits the entire digital ecosystem.

Defining and operationalizing consumer engagement has been the source of considerable disagreement in advertising and marketing literature, and the recent surge in research attempting to conceptualize brand engagement via social media has reinvigorated the debate. Maslowska, Malthouse, and Collinger (2016), for example, offer a detailed literature review, concluding a lack of consensus in academia or practice on engagement. Examining literature on consumer engagement in social media, Barger, Peltier, and Schultz (2016) came to a similar conclusion. Much of the literature conceptualizes engagement as a psychological process or state (Bowden 2009; Brodie et al. 2011; Calder, Malthouse, and Schaedel 2009). Higgins and Scholer (2009, p. 102) define the concept as “a state of being involved, occupied, fully absorbed, or engrossed in something.” Another body of literature operationalizes engagement as behavioral manifestations of consumer–brand relationships (CBRs), referred to as consumer engagement behaviors (CEBs; Bijnont et al. 2010; Van Doorn et al. 2010; Kumar et al. 2010). Still others talk about engagement in terms of brand messages provoking affective, passionate responses from consumers and facilitating co-creative experiences (Gambetti, Graffigna, and Biraghi 2012).

Increasingly, a consensus has emerged around the notion of consumer engagement as a multidimensional concept encompassing cognitive, emotional, behavioral, and social components of consumer–brand
interactions beyond mere exposure (Calder, Isaac, et al. 2016; Gambetti, Graffigna, and Biraghi 2012; Hollebeek, Srivastava, and Chen 2019; Vivek, Beatty, and Morgan 2012). In fact, Hollebeek, Srivastava, and Chen (2019) revised previous definitions referring to engagement in terms of consumers’ volitional investment of cognitive, emotional, behavioral, and social resources into brand interactions. Still, a recent study testing Hollebeek, Glynn, and Brodie’s (2014) widely used consumer–brand engagement scale points to discriminant and face validity issues for cognitive and affective components of the scale; their analysis, along with that of an expert panel, concluded that the measure failed to encapsulate concepts such as self–brand connection and brand attachment, leading the researchers to conclude that engagement is solely behavior based (Obilo, Chefor, and Saleh 2020).

To delineate a path forward for interaction planning, we must first reconcile these competing perspectives in a way that can inform. We concur with Van Doorn et al.’s (2010) conceptualization of CEBs, wherein cognitive, affective, and social factors influence CEB decisions in an iterative manner. However, greater understanding of how CEB levels change over time because of CBR evolution as well as how other actors are impacted is needed.

Social exchange theory (SET) has been instrumental in conceptualizing interpersonal and consumer–brand relationship development through exchange (Fournier 1998; Hayes, King, and Ramirez 2016) and offers a useful lens in examining the behavioral manifestations of CBRs (CEBs; Gummerus et al. 2012; Van Doorn et al. 2010) with implications for computational advertising. SET explains that relationships develop and evolve through continuous net-positive exchanges between partners, leading to the emergence of trust, emotional attachment, and intrinsic value being ascribed to the relationship; these elements as well as the totality of exchanges impact future interactions (Cook and Yamagishi 1992; Frenzen and Nakamoto 1993; Molm, Takahashi, and Peterson 2000). As a result, affective and behavioral commitment to the relationship leads actors to continue with such exchange with a partner—often irrationally, even at considerable opportunity cost, to ensure continued receipt of intrinsic and/or extrinsic benefits (Molm, Takahashi, and Peterson 2000).

From a brand perspective, CBRs are multidimensional constructs composed of the parallel components of brand satisfaction and brand trust (Fournier 1998). Brand satisfaction develops through multiple consumer–brand interactions resulting in overall positive perceptions of brand quality and reliability, though some interactions may be positive while others are negative. Ongoing net satisfactory exchanges lead consumers to believe that the brand will act with integrity and in their best interest, generating brand trust. Through the combination of brand satisfaction and trust, a positive transactional consumer–brand dynamic transforms into a committed personal relationship, with emotional attachment and intrinsic value being ascribed to the brand (Hess and Story 2005). So, as in interpersonal relationships, consumer–brand interactions (e.g., CEBs) are functions of perceived cost-benefit analyses wherein those involved seek to maximize benefit and reduce uncertainty based on previous interactions (Hess and Story; Morgan and Hunt 1994).

From the SET standpoint, then, consumer engagement is a dynamic, iterative process wherein consumers and brands must each weigh the costs and benefits of CEBs for themselves and other actors. This is in line with Van Doorn et al.’s perspective (2010), while providing a deeper understanding of relationship development over time. When making CEB decisions, consumers account for cognitive factors (e.g., satisfaction, consumption goals, identity, uncertainty), affective factors (e.g., trust/commitment, brand attachment), and social factors (e.g., social follow response, reputation) in determining perceived values of behaviors. The outcome of CEBs will be integrated into the ongoing calculus of the CBR, which includes all positive and negative brand interactions. Brands must also calculate the value of CEBs based on their congruence with brand strategy and expected brand outcomes. An important aspect, however, is that each must perceive the sum of consumer–brand interactions as positive and equitable to maintain the relationship over time; too many or extremely negative interactions upset the value proposition, leading to disengagement (Hayes and King 2014; Thibaut and Kelly 1959).

Taking this view of consumer engagement, a more holistic approach to interaction planning must emerge that (1) integrates all consumer–brand interactions across available engagement arenas and assets, (2) considers the costs and benefits for all actors involved when making “placement” decisions, and (3) accounts for actions taken by each actor. In this sense, current approaches to computational advertising primarily focusing on programmatic processes suffer from drawbacks regarding a holistic approach to fostering consumer engagement.
First, success typically focuses on short-term considerations, often without accounting for long-term goals. A 2018 survey of global marketers shows that short-term goals such as sales, impressions, or reach are reported among the top effectiveness metrics, yet long-term outcomes such as brand loyalty are not mentioned (Lambert 2018). Academic research follows a similar trend (Boerman, Kruikemeier, and Zuiderveen Borgesius 2017; Yun et al. 2020). One way to overcome this challenge is to find creative ways to incorporate the impact of social media in the traditional marketing mix model. For example, Fulgoni (2015) illustrates how brands can use social media to amplify the impact of traditional media.

Second, and perhaps most important, current approaches focus on brand outcomes without consideration of outcomes for the consumer. To account for both short- and long-term brand goals, computational advertising must account for the costs and benefits associated with each consumer–brand interaction as experienced by the consumer as well as by the brand, benefiting the ecosystem as a whole. As discussed, CEBs are behavioral manifestations of CBRs, built and strengthened through ongoing, positive, and equitable exchanges (Hayes and King 2014). For each interaction, advertisers must consider implications for the brand, their consumers, and other consumers connected to their consumers (Maslowska, Malthouse, and Collinger 2016). Advertisers must also consider how their interactions with consumers influence (or are influenced by) other actors in this ecosystem. Fostering engagement with positive outcomes for all stakeholders leads, in principle, to realization of long-term goals, such as brand associations, trust, attachment, and loyalty (Fournier 1998; Hayes and King 2014; Hess and Story 2005; Vivek, Beatty, and Morgan 2012). Advertisers need also to consider how this ecosystem creates a new playing field where competing interests—not only from their competitors but also from influencers, platforms, and other consumers—become visible and intertwined.

Algorithms must, therefore, model costs and benefits for each potential engagement behavior for each actor and select the optimal mix to generate the most value for all relevant actors, sustaining long-term CBRs, and thereby garnering long-term benefits for brands and consumers. As Figure 2 depicts, consumers consider their existing relationship with the brand and a variety of cognitive, affective, and social factors before choosing to engage or not to engage. Brand value of CEBs depends on congruence with strategy, expected brand outcomes, and a variety of contextual factors (e.g., platform rules and capabilities). The outcomes of CEBs for the consumer and the brand will feed into the ongoing CBR calculus, strengthening or weakening the relationship. For each CEB, consumer and brand outcomes as well as the resulting change in CBR will iteratively inform future decisions. Therefore, computational advertising approaches must continually track changes in each factor weighing into placement values for consumers and the brand. Algorithms are driven by the data that informs them. Measurement is vital.

Measurement

Reaching the right audience at the right time through the most effective and efficient medium has long been
at the heart of media buying and selling. To do that, measuring target audiences accurately and reliably is crucial. Among various metrics, exposure has been the traditional advertising currency. The audience measurement industry in the United States has evolved around exposure-based metrics, such as ratings, shares, reach, and impressions (for a history, see Kim 2018). Although counting eyeballs is likely to remain the most important indicator given long-standing business conventions, recent discussions focus on improving measurement standards by increasing accuracy and consistency across platforms and incorporating measures beyond exposure in the age of computational advertising. With the evolution of the four A’s (arenas, assets, actors, and actions), key measurement issues include understanding the fundamental changes in the current exposure-based measurement system and developing new ways of quantifying and measuring actions by multiple actors across different arenas, particularly consumer engagement and experience. In doing so, computational methods can leverage both structured and unstructured digital trace data to conduct cost-benefit analyses throughout the customer journey (Liu-Thompson et al. 2020; Yun et al. 2020).

Within the realm of exposure-based measurement, the emergence of such a complex ecosystem has complicated traditional ways of measuring audiences. Advertisers have called for a better way to measure exposure to variations of digital content that are comparable across platforms and devices, thus creating an “apples-to-apples” way of tracking their measurements (Lafayette 2019, September 4). Responding to the growing needs for comparable cross-platform metrics, the Media Research Council (MRC) announced cross-platform standards that work for variations of video content (e.g., linear TV, video on demand [VOD], over the top [OTT], streaming) in 2019 (MRC 2019). This new, impression-based measurement, to be fully implemented by 2021, emphasizes comparability across platforms, especially digital media and television. More importantly, the MRC plans to propose outcome-based metrics (e.g., brand lift, sales lift, return on investment [ROI]) that can be combined with impression metrics in the coming years (Mandese 2019).

More fundamental changes in measuring actions in the new digital ecosystem have been made possible by the ability to collect and analyze various forms of user data on a real-time basis. Advertisers—or at least platforms—can now capture individuals’ digital trace data from exposure to content, to comments on ad messages, and potentially link to past purchase or nonpurchase brand-related behaviors, which opens up new avenues for measurement and, to an extent, using such measures at an individual level to personalize interactions. In addition, we observe the development of innovative approaches to measuring consumers’ reactions in the form of neurophysiological measures such as biometrics, eye tracking, and functional magnetic resonance imaging (fMRI; Venkatraman et al. 2015). All these changes suggest that we can extract insights from measures beyond exposure, such as consumer engagement and experience, and move toward a holistic understanding of consumer interactions with content, brands, other consumers, and platforms, as well as outcomes of these interactions. However, these changes come with caveats: The capabilities of measuring consumer actions beyond exposure do not necessarily mean that this can create a 360-degree understanding of consumers. As Fulgoni (2018) acutely notes, the increasing limits on data access due to the platforms’ walled gardens and privacy regulations make it more difficult to estimate marketing mix models accurately and, we argue, also to implement more effective personalization.

Despite these limits, providing a conceptual framework of what can be measured beyond exposure helps us to think through what actions by which actors can be tracked in which arena to ultimately use it as assets. As discussed earlier, this ecosystem includes multiple actors and actions across multiple touch points (Maslowska, Malthouse, and Collinger 2016). Given that media is characterized as a dual-product market with content sold to audiences and audiences, then sold to advertisers, CEBs in two dimensions seem most relevant in relation to what to measure and which to include in cost-benefit analyses. The first dimension includes media engagement behaviors (i.e., behaviors that manifest the degree to which audiences are immersed in consumption of media content or interactive communication platforms and presumably advertising messages placed in those content offerings or platforms). The next dimension includes brand engagement behaviors (i.e., behaviors that demonstrate the extent to which individual consumers make a meaningful connection with a brand and/or other consumers of the brand) (Chan-Olmsted and Wolter 2018).

We adopt the three stages of dialogue behaviors proposed in Maslowska, Malthouse, and Collinger (2016), namely, observing, participating, and co-creating as the levels of engagement, and apply them to these two dimensions of engagement behaviors—
brand and media—as shown in Figure 3. Observing is the lowest level of interaction, where consumers are passively exposed to media content or brand-initiated messages. Participating involves chiming into conversations. This level of interaction is reflected in people’s response behaviors, for example, sharing media content or brand-initiated messages via social media, expressing emotions in the form of likes, thumbs-up, or other indicators (e.g., angry faces), or generating eWOM. Co-creation represents the highest engagement level and invites consumers to be producers. They can create memes or reaction videos to the content they consume or commercials they encounter, or participate in brand-initiated promotions, reflecting on the meaning of the brand in their daily lives (Malthouse et al. 2016). All these behaviors, most of which occur in digital platforms, are traceable and quantifiable by using social media analytics, data-mining techniques, and algorithms (see CA-UGC (Liu-Thompkins et al. 2020) for an in-depth discussion on the user roles in CA and how each role can be better understood by computational approaches).

Yet as discussed earlier and elsewhere in this special issue (Yun et al. 2020), most engagement measures suffer from their focus on short-term goals. In this regard, customer experience is a related concept that attempts to capture a customer’s overall responses to brand-related stimuli throughout the journey (Brakus, Schmitt, and Zarantonello 2009), thus having a more holistic basis for measurement. Scholars note the multidimensional nature of customer experience and its temporal aspect. In their review, Lemon and Verhoef (2016) conclude that customer experience is “a multidimensional construct focusing on a customer’s cognitive, emotional, behavioral, sensorial, and social responses to a firm’s offerings during the customer’s entire purchase journey” (p. 71). They highlight the lack of robust measurement approaches across the customer journey (i.e., prepurchase, purchase, postpurchase) and the difficulty of developing a single set of measures across different industries and touch points.

Although fully conceptualizing experience is beyond the scope of this article, we argue that experience differs from engagement in that experience is a more holistic, context-free, and long-term-oriented process. As noted by Calder, Malthouse, et al. (2016), engagement results from experiencing a brand as related to some higher-order personal life goal or value. Another study by Calder, Isaac, et al. (2016) suggests a way to solve the problem of establishing a single measure for customer experience. They propose a flexible approach that measures context-specific experiences that can vary across brands and products. They identify five broad categories of experiences (interaction, transportation, discovery, identity, and civic orientation) and demonstrate how certain dimensions of these experiences are more or less prevalent in one product category versus another and how these context-specific measures of experiences predict consumption behaviors.

Given that the future of advertising is less about purchasing (potential) exposure and more about fostering engagement through interaction planning, the next step in computational advertising is to further develop measures for context-specific experience across media channels and brands at each stage of the consumer journey. Also, it is important to understand
how brand and media engagement behaviors laid out in Figure 3 contribute to specific dimensions of consumer experience and brand outcomes such as attitudes, trust, loyalty, and purchase. For example, if civic orientation is a dimension that is more important in news products, news organizations can examine how observing (e.g., reading news), participating (e.g., commenting on news), or co-creating (e.g., blogging about the news) influences news consumers’ experiences with the news product from a short-term perspective (e.g., page views, click-through rates) and a long-term perspective (e.g., trust in the news, journalists, news organization, renewed subscriptions). As mentioned in (Yun et al. 2020), measurement is now an integral part in the era of computational advertising from creating, executing, and evaluating advertising programs. The challenges in this new digital ecosystem are not merely about lack of proper data but the potential abundance of data and increasingly limited data access (Fulgoni 2018). Extracting insights and using them to achieve short- and/or long-term goals of brands and consumers will depend on clearly identifying what the goals of brands and consumers are, what value brands intend to offer and consumers seek out, and what outcome measures best capture the success of intended goals (see Figure 2), all of which are in the realm of interaction planning to foster engagement.

Fostering Engagement with Interaction Planning

With the emerging new digital ecosystem, the ability to link CEBs to exposure to advertising has dramatically increased. Instead of just looking at the costs of exposure, we can now look at the costs associated with getting a viewer to click on an ad or browse a website or add a product to a shopping cart or purchase a product. This attribution process is relatively straightforward when the product is inexpensive and/or simple and the purchasing process is linear and takes place over a short time period. Attribution gets more complicated when product cost and complexity rise and the process involves multiple devices and multiple touch points over an extended period.

Technological advances have and will continue to enable new ways of interaction planning. More types of advertising will likely become available programmatically as devices ranging from the digital display devices to wearables to digital speakers become connected and addressable. Other technologies may help address some current problems—advertising fraud, attribution modeling, and cross-device identity resolution—but the conceptual model for planning in the current media marketplace may merit fundamental rethinking, moving away from media planning toward interaction planning, with a focus on fostering engagement.

As discussed, this alternative conceptual model focuses on how brands can foster a broad range of CEBs, in addition to purchase (Maslowska, Malthouse, and Collinger 2016). In this alternative model, a brand-initiated message that causes the audience to fill out surveys about the brand or blog about the brand or consume brand-related content becomes important and worthy of investment, and the advertiser’s media planning process should keep these objectives (i.e., fostering engagement) in mind. We revisit the three levels of consumer actions that can be observed and measured in the digital ecosystem (see Figure 3) and suggest ways in which we can foster these different types of engagement behaviors.

To promote exposure to brand-initiated content or media content, the conventional way of reaching the target audience by mass media still seems valid. Television (including streaming services) continues to be a medium that can generate high reach and frequency in a short period of time. Brands can first use mass media to circulate their message to a wider audience, then build further reach and frequency via social media that are popular among the target audiences, making use of the dialogical affordances from this arena. Conversely, brands can create a social media campaign that is popular or shareworthy so that it can be picked up by mass media (Fulgoni 2015). The growth of connected and addressable TV may help consumers feel less irritated by irrelevant TV advertising. Addressable TV can also help brands reduce unnecessary media spend by presenting the relevant ads to specific target audiences (Taylor 2019).

To foster higher levels of engagement, such as conversation with brands and/or other consumers or consumers’ co-creation, a focus on understanding the impact of brand-initiated messages on consumer engagement and the long-term value of greater levels of consumer engagement is needed. Interaction planning begins with a consumer engagement architecture, is supported by consumer engagement attribution models, and is measured through a consumer engagement index. This changes how advertisers evaluate and plan their portfolios. While we have argued that the focus for advertising needs to shift from exposure to engagement, we also believe that this will be accompanied by a shift in the types of media
purchased (or other interactions planned), the manner in which messages are delivered, and the ways that ads (or other actions) are placed or executed.

First, we expect to see more of a focus on conversations between brands and consumers or among consumers, where these conversations help consumers sort through complex choices among offerings, order products, use products, and obtain postpurchase support. This will mean a greater emphasis on new ad platforms that facilitate conversations like voice-activated virtual assistants and messaging applications (Copulsky 2019; Sotolongo and Copulsky 2018) or social media channels where consumers themselves can exchange information or be connected with one another, forming a community based on similar tastes or interest in brands. Second, because voice search may become a significant entry point for conversational marketing, this will require a new approach for ad placement, akin to what exists for text-based paid search and search engine optimization. Third, message delivery will be tempered by contextual considerations, underscoring the importance of delivering messages in contexts befitting the consideration-purchase-use cycle. This includes factors such as time and location (Lian, Cha, and Xu 2019). It also includes the need for ongoing considerations about where brand messages are being placed (even if programmatically), as evident from discussions about advertising supporting mis- and disinformation websites (Mills, Pitt, and Ferguson 2019, Braun and Eklund 2019), or even recent boycotts or actions to dissociate one’s brand from specific social media platforms or channels.

All these considerations point toward this new conceptual model where the goal is planning for the right set of interactions among actors within arenas making use of the right assets to motivate the desired actions. This new conceptual model places a greater onus on brands to truly understand the entire customer journey and how this journey varies among different types of consumers. Computational advertising can help optimize interaction planning strategies by identifying where, when, and how to foster engagement rather than merely placing brand-initiated messages across different touch points. Some of the insights needed for interaction planning in this new environment will come from the digital trace data generated by consumers as part of their customer journeys. Other insights will be generated through greater testing with a rapidly compressed time frame for obtaining and analyzing the results of tests. By necessity, interaction planning may come to look more and more like agile marketing (Edelman, Heller, and Spittael 2016).

**Crosscutting Issues in Computational Advertising**

Our discussion so far has been about the digital ecosystem, the evolving role of traditional players, and the emerging roles of new ones. We now focus on issues that affect all components of the digital ecosystem.

**Ethics, Privacy, and Power**

Platforms collect vast amounts of data about individuals, giving them tremendous power to reach individuals with a level of microtargeting heretofore unimaginable, with some of this power also being available to advertisers. This leads to a power shift, with platforms assuming an increasingly central role in the ecosystem. Recognizing the tremendous power of platforms (Marantz 2020), there have been a slew of recent efforts to start discussions on this topic within the academic community. An example is the fairness, accountability, transparency, and ethics (FATE) initiative that is being actively researched by prominent groups (Microsoft 2020). Moreover, the balance of power among platforms, advertisers, and consumers requires special attention. This is particularly the case in matters of attribution of responsibility and platform governance (Helberger, Pierson, and Poell 2018). There is a need, therefore, for serious discussions among all involved parties, including consumer advocates; it is also warranted when considering privacy discussions and the legal and regulatory framework more broadly (Helberger et al. 2020).

**Security and Vulnerability**

Platforms collect vast amounts of data about individuals, including demographic and behavioral information, thus creating a huge risk of security breaches (Kim 2012). There are also several vulnerabilities that are unique to computational advertising. First, the agreed-upon terms of a specific advertising contract could be prevented from being fulfilled. An example is the contention that the owner of the platform may manipulate the search rankings of the advertisements of brands, and thus the affected advertisers would not get the full value of their ad spends. This is the contention of a recent lawsuit (i.e., Dreamstime 2018).

Second, one of the challenges in today’s digital ecosystem for interaction planning is fraud. In some cases, the publishing sites themselves are fraudulent; in other cases, the purported audiences are fake. Indeed, both fake sites and fake audiences can occur.
Even when this is not a problem, understanding audiences is challenging when multiple individuals use the same browser on a shared computer, a single individual uses multiple devices, cookies are deleted or not accepted, in addition to manipulations incurred by bots or spiders (Kim 2018). Moreover, a brand may use click farms to fool the search-ranking results of the advertising platform and artificially boost ratings (Malthouse and Li 2017); to post fake positive reviews of one’s own product; or to post fake negative reviews of a competitor’s product. These actions impact rating sites like TripAdvisor (Schuckert, Liu, and Law 2016). Finally, misinformation and disinformation campaigns on digital platforms spread rumors and other misleading messages, as seen in several political campaigns (Venturini and Rogers 2019).

Feedback and Learning
Arenas in the digital ecosystems are dynamic: They continuously observe the interactions among actors, analyze and evaluate them in terms of fitness toward some objective, and learn. Their learning can include understanding strategies that various actors use and how effective they are, discovering how to optimize revenue or to improve pricing models, and so on. This could in principle be done manually (e.g., an advertiser analyzing performance of campaigns on a dashboard), but such a learning cycle is drastically accelerated and expanded with machine learning and other implementations of AI. As various actors get experience, they are likely to change their behaviors to optimize their own respective objectives. This causes the environment to evolve, and adaptation may be required to remain competitive. This can be seen from a game theory perspective, where the system moves from one “quasi-equilibrium” to another, as each actor tries to optimize its objective function, in what may in essence be a zero-sum game (Ansari, Chan, and Yang 2004). Each actor as well as the platform can use techniques like reinforcement learning to continually adapt its behavior as a response to the changing environment (Zhao et al. 2017). There is, therefore, growing attention for modeling this computational advertising dynamic (Jørgensen and Zaccour 2014; Viscolani 2012; Ling and Lawler 2001).

Concluding Comments: Toward a Research Agenda
The shift from traditional to computational advertising in an increasingly complex digital ecosystem brings exciting opportunities and important challenges for decisions about when, where, and how to get a brand’s message to its intended audience. Moving away from merely purchasing exposure, advertisers need to consider how to plan interactions aiming at fostering engagement with consumers, accounting for the new actors, actions, arenas, and assets that can influence—positively or negatively—the consumer–brand relationship. These changes call for innovative, interdisciplinary, comprehensive, and ambitious research on computational advertising and its implications, in several directions. We, therefore, conclude this article with a series of thoughts toward a research agenda for interaction planning and fostering engagement within a computational advertising era.

First, the emergence of the digital ecosystem itself, and its implications for (computational) advertising, calls for research. Datafication continues to take over an increasing share of social processes at a fast speed, while AI and related technologies (as seen in the rise of recommender systems, conversational interfaces, and the widespread use of machine learning) gain an increasingly prominent role in shaping the digital ecosystem in which we now “live.” On one hand, this evolution can be seen as an exciting opportunity that calls for a deeper understanding of how advertisers can best manage the ever-expanding set of places of interactions with consumers (engagement arenas), while also requiring a serious rethinking of what a media plan may look like in times of accelerated convergence and accounting for a complex dynamic among actors and actions in this fast-evolving and interdependent ecosystem. As new actors (for example, influencers) and actions emerge, how can they be integrated to interaction planning, and with what assets? How can brands handle the complex and dynamic nature of the interactions among these new actors, consumers, and the brand itself? Under which circumstances should brands make use of new actions afforded by technology developments, and when should brands abstain?

On the other hand, the emergence of the digital ecosystem also brings broader questions about power dynamics, as well as normative and ethical concerns. What are the limits to repurposing data collected through these new processes? How can adequate consumer consent be ensured? What are the consequences of the shift in power among brands, consumers, and platforms for planning decisions? What is the (often-hidden) influence of platforms in shaping the system, and how should their actions and increasing dominance be accounted for? As brand messages (or
interactions) are increasingly placed automatically, what are the responsibilities from advertisers, and how should they execute (automated) interaction planning responsibly and in a way that shores up consumer trust?

Second, focusing on consumer engagement, the shift toward fostering engagement necessitates a deeper understanding of consumer–brand interactions. For exposure, advertisers previously needed to know simply that consumers saw the brand content; now, it is crucial to understand why consumers engaged in brand-related behaviors. So, what are the nonbehavioral (cognitive, affective, and social) dimensions of engagement that influence engagement behaviors? How do they interact to influence CEB-based contexts such as platform and product category? As consumer–brand relationships strengthen, how do the weights of different factors shift, thus changing the CEB decision calculus? What are the limitations to computational approaches in terms of gathering and integrating the necessary data to measure long-term goals, including brand trust, attachment, or loyalty? What capabilities need to be developed to facilitate modeling consumer engagement behaviors and their outcomes?

Third, when it comes to measurement, with increasing concerns surrounding the use of personal data for behavioral targeting, privacy laws such as the European Union’s General Data Protection Regulation (GDPR) or the California Consumer Privacy Act (CCPA) limit the collection, storage, and use of consumers’ personal data. Assuming that this type of regulation will be implemented more widely, how this will change measurement practices? From a consumer’s viewpoint, the trade-off between the benefits of personalized experiences and privacy concerns needs further investigation. To what extent are consumers willing to be measured, to let their data become available to advertisers, or to engage in interactions initiated by brands based on these data? How can advertisers offer value in exchange for consumers’ personal data in a less intrusive and more ethical and responsible manner? Last, when we shift the focus of media planning toward fostering engagement, what are some of the longer-term outcomes beyond click-through rates, number of likes, or conversion rates? What are, and how will we measure, the long-term goals for (especially) consumers and quantify the effectiveness of fostering engagement on these long-term goals? And how can advertisers effectively make sense of and get access to relevant data in a responsible manner?

Fourth, for interaction planning and fostering engagement, one area of concern is attribution. To strengthen CBRs, interaction planning models need to maximize positive engagement instances and minimize negative engagement instances. This necessitates a comprehensive understanding of how each actor will respond to each possible action and asset employed in each arena. When, where, how, and why are interactions perceived as positive and negative? What is the magnitude of the positivity and negativity for various actions and assets? How can we understand which types of brand actions drive outcomes that matter? How do various combinations of brand actions change these outcomes and over what time span? How do these attributions change as the CBR develops, introducing more emotion into the cost-benefit analysis? Are there differences in the effectiveness of actions and assets at different stages of the CBR, and how sensitive are CBRs to negative interactions potentially leading to disengagement at various stages of the CBR?

While the issue of attribution encompasses several aspects of the advertising process, it points to a larger set of challenges in interaction planning. For instance, how can brands plan meaningful interactions with consumers, and what is the ideal combination of actions, assets, and arenas for each stage of the customer life cycle? And how does the process of interaction planning differ among product or service categories? Importantly, how can we integrate the role of advertising creatives in this process? Although ad creativity is beyond the scope of this article, how brand- or consumer-initiated messages interact with contextual factors (including the arena and assets in which they take place) to influence engagement needs further investigation. Moreover, much must still be researched regarding the effectiveness and limits of personalization in such an ecosystem, especially for placement decisions within and across arenas.

Finally, and looking at advertising research more broadly, we acknowledge the complexity and dynamic nature of the digital ecosystem in the computational advertising era, in a time of fast-paced societal change and increasing calls for transparency, responsibility, and open science. This requires advertising scholars to engage in interdisciplinary efforts with such fields as computer science, law, and social sciences more broadly (among many other fields), and, with practice, as a way to inspire not only what to investigate but especially how to conduct innovative, ambitious, and responsible advertising research in this new computational advertising era.
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