Communicating Algorithmic Process in Online Behavioral Advertising

Motahhare Eslami[1,2], Sneha R. Krishna Kumaran[1], Christian Sandvig[3], Karrie Karahalios [1,2]
[1]University of Illinois at Urbana-Champaign, [2]Adobe Research, [3]University of Michigan
[1]{eslamim2, srkrish2, kkarahal}@illinois.edu, [2]{meslamim, karrie}@adobe.com, [3]csandvig@umich.edu

ABSTRACT
Advertisers develop algorithms to select the most relevant advertisements for users. However, the opacity of these algorithms, along with their potential for violating user privacy, has decreased user trust and preference in behavioral advertising. To mitigate this, advertisers have started to communicate algorithmic processes in behavioral advertising. However, how revealing parts of the algorithmic process affects users' perceptions towards ads and platforms is still an open question. To investigate this, we exposed 32 users to why an ad is shown to them, what advertising algorithms infer about them, and how advertisers use this information. Users preferred interpretable, non-creepy explanations about why an ad is presented, along with a recognizable link to their identity. We further found that exposing users to their algorithmically-derived attributes led to algorithm disillusionment—users found that advertising algorithms they thought were perfect were far from it. We propose design implications to effectively communicate information about advertising algorithms.

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H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

Author Keywords
Advertising Algorithms; Algorithmic Transparency; Process Communication; Ad Explanation; Algorithmic Authority

INTRODUCTION
The opacity of advertising algorithms, along with their potential for violating user privacy, has resulted in a call for algorithmic transparency—a call to communicate how an ad is tailored to users. Advertising is the primary means of financing Internet services, although for some it is one of the least favorite aspects of the online experience. To increase the effectiveness of advertising, marketers have started to use behavioral targeting, which algorithmically infers who likes what by collecting users' behavior [4]. However, the opacity of algorithmic ad tailoring has raised privacy concerns and decreased user trust in advertisers. Researchers, activists, and regulators argue that if advertisers want positive relationships with their potential customers, advertisers must clearly communicate their algorithmic ad curation process [51, 53].

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Many advertising platforms now give users the opportunity to learn about ad tailoring processes by showing more information when users click on a question like "Why am I seeing this ad?" [24, 25]. However, algorithmic transparency is not straightforward. Explaining a complex algorithm's behavior accurately, comprehensively, and briefly in a non-technical way is challenging [46]. Even in cases where it is easy to provide users with an interpretable explanation about an algorithmic curation process, providing explanations is not an unmitigated good. For example, providing students with too much or too little information about a grading algorithm both diminished students' trust in the grading system [29]. Explanations are more challenging in behavioral advertising because revealing curation processes may create new privacy concerns [44, 49]. How revealing aspects of the algorithmic ad curation process will affect user perception of behavioral advertising remains an open question.

We take a first step toward addressing this question by conducting a qualitative user study in which we exposed 32 users to three distinct lenses in online behavioral advertising: 1) *why* a specific ad is shown to them, 2) *what* attributes an advertising algorithm infers about them, and 3) *how* an advertiser uses this information to target users. Through this process, we investigated participants' perceptions of different communication mechanisms in online behavioral advertising. We then evaluated how users desired the inner workings of the advertising algorithmic process to be reflected in their ad experience.

We discovered that vague and oversimplified language made many existing ad explanations uninterpretable and sometimes untrustworthy. Participants were most satisfied with explanations that included specific information that an advertiser used to target an ad. However, participants did not wish to see information that they considered "creepy". They also preferred explanations that related to an important and recognizable part of their identity. Participants were especially appreciative when these valued traits were inferred by an algorithm.

We learned that disclosing algorithmically-inferred interests, particularly those that are wrongly inferred, can lead users who assumed algorithmic authority—that advertising algorithms are perceptive, powerful, and sometimes scary—to algorithm disillusionment—that algorithms are not scary and powerful, or even effective. We conclude the paper with design implications which can provide users with a more informed, honest, *and* satisfying interaction with their personalized ads.

COMMUNICATING ALGORITHMIC PROCESS

Most algorithmic decision-making systems do not communicate their inner workings to users [39], resulting in information asymmetry—a disparity in what is visible to different parties to a system [34]. While this opacity partly stems from the desire to protect intellectual property, it is also a strategy to provide users with a seamless and effortless interaction [5, 13]. This has recently been called into question after researchers and activists have revealed biased, discriminatory, and privacy-violating algorithmic systems [19, 43, 46, 15]. Therefore, researchers, activists, and governments have called for "process communication" to satisfy a user's "right to explanation" of hidden computation that affects them [11, 20, 56].

The Complexity of Transparency

Communicating more information about an algorithmic process can improve interaction. In social media, users who were made aware of a curation algorithm engaged more with their algorithmically-curated feeds [14]. Recommender systems incorporating explanations produced more user acceptance of, confidence in and trust in recommendations than those without explanations [47, 21, 40, 54]. But explanations come in different forms, from justifying the motivations behind a system without disclosing how the algorithmic decision is made to detailing the steps an algorithm takes to produce a recommendation [18]. Increased process communication has also been recommended for social matching systems [28], team formation tools [26], rating platforms [15], and algorithmic journalism [12] to build informed and trustworthy interactions between users and systems; and yet effectively revealing an algorithmic process is a serious challenge.

Communicating an algorithmic process can be detrimental. Returning to the grading example from the introduction [29], Kizilcec showed that providing students with high transparency (i.e. revealing the existence of a grading algorithm, along with students' raw grades) was as harmful as providing students with low transparency (no information about the existence of a grading algorithm). Both conditions confused students, violated their expectation of the system's outputs, and therefore, eroded their trust in the system.

More cynically, explanations may not be intended to explain. "Explanations" of ranking and scoring systems in finance have historically been designed to obscure the actual operation of the algorithm (e.g., credit scores) [39]. Internet platforms implement some functionality as a signal to regulators and critics, offering the minimum required to forestall further action [33]. These transparency features are more useful to forestall regulators than to help the users whose data is collected: the US data brokerage industry's transparency applications (e.g., "About the Data") may be one example [10]. Online content platforms, as intermediaries between advertisers and audiences, may not wish to explain their personalization algorithms to users because they need to avoid explaining them to advertisers [52], potentially because they do not work well [45].

Process Communication in Online Behavioral Advertising

Turning to prior work specifically about behavioral advertising, researchers have found that a user's lack of information about personalized ad tailoring can result in mixed feelings towards ads in general [49, 53]. Users hold inaccurate or incomplete "folk models" about how online behavioral advertising works [41, 58]. Sometimes, users believe that advertising algorithms collect more data than they actually do, causing privacy concerns [53]. Recent work has shown that when advertisers do provide some information about how ads are tailoring, it is incomplete, vague, and misleading [2].

This failure to communicate algorithmic processes to users [31] has resulted in efforts by researchers and activists to reverse-engineer ad targeting mechanisms [32, 38] to give users control over their ads and to inform them of who tracks them [1]. Researchers also have built tools like Floodwatch [37] and visualizations like "Behind the Banner" [16] that create a multi-faceted view of ads to inform users of data advertisers might collect [3] and what can be inferred from that data [57]. As another strategy, ProPublica's browser plugin "What Facebook Thinks You Like" collects information from the Ad Preferences settings page [27].

These approaches have usually resulted in more negative attitudes towards behavioral advertising. Using browser plugins that make users aware of existing tracking practices in online advertising [44] or informing users about the types of personal data advertisers use to tailor ads [42, 49] has increased users' privacy concerns and decreased their trust and preference in behavioral advertising. However, these disclosures were all from third-parties, not advertisers themselves. Therefore, it remains unknown how users would perceive personalized ads if effective disclosures came from the advertisers themselves as a sign of effort to provide transparency and trust.

Research Questions

In this study, we began to investigate the communication of algorithmic processes in online behavioral advertising. We first explored how advertisers currently choose to communicate the algorithmic process to users. Usually this communication is in the form of an option such as "AdChoices", "Why am I seeing this ad?", "Why this ad?", etc. We call this an ad explanation (see Figures 4, 5, and 6 for examples). To understand the effectiveness of these techniques, we asked:

RQ1: a) How do users perceive and evaluate existing ad explanations? b) Given the opportunity to craft their own ad explanations, how do users' preferred ad explanations compare to the existing ad explanations?

The existing ad explanations, however, only disclose the tip of the behavioral advertising iceberg. To tailor ads to users, advertising algorithms analyze user behavior to build a profile for users that includes their attributes and interests. While usually hidden, a few advertisers have started to disclose these inferred profiles, or at least a part of them (Figure 1). Advertisers interact with these algorithmically-derived attributes to identify their desired audience via an ad targeting interface (Figure 2). These advertiser interfaces often provide more information about what is happening inside the black box of online advertising than information intended for users; however, they are usually not easily visible to users. Therefore, we asked:

RQ2: When exposed to typically hidden inner attributes of an algorithmic advertising platform (such as users' algorithmically-derived attributes and how advertisers use them), how do users think about and evaluate these attributes?

STUDY DESIGN

We conducted a lab study in which we exposed 32 Internet users to different disclosures about how their online ads are tailored to them and interviewed them about the experience. First, users viewed their actual personalized ads and the explanations given by advertisers about why they were seeing those ads. We call this the *Ad Explanation View*. Next, users saw a view that showed what an advertising algorithm has inferred about them—the *Algorithm View*. Finally, users used an ad creation interface to experience creating an advertisement in the *Advertiser View*. In this phase, users were asked to imagine an audience that they belonged to for a specific product and target it. Following both the Ad Explanation View and the Advertiser View, users wrote their own desired explanation for a product of interest. We called this a *Speculative Design Task*. All interviews (of one and a half to three hour duration) were audio recorded and transcribed for analysis.

The Ad Explanation View

We started the study with a pre-interview to understand participants' understanding of and opinions about behavioral advertising. We first asked participants whether they found advertising useful and how they usually interact with their ads. Next, we explained the practice of behavioral advertising to participants who were not previously aware. We then evaluated participants' awareness of existing ad explanations (see Figures 4, 5, and 6 for examples). If a participant was aware of these explanations, we asked if they could point to any explanations on their own ads. If they were not, we showed the participant ad explanations on popular public sites.

In the next step, we sought participants' opinions on some existing ad explanations. For ecological validity, we asked participants to view ads and the ads' explanations (if present) on a browser of their own personal device (laptop, tablet, or smartphone). In this way, participants could see ads that were actually tailored to them and that reflected the interests and attributes inferred by real systems.

Participants were free to view any site where they usually see ads. If they could not think of one, we suggested news and social media sites that usually contain ads. For each ad a participant chose to discuss, we asked if they thought it was generic or personalized. If they believed the ad was personalized, we asked why they thought it was shown to them. Participants then offered their opinion on the ad explanation (if present) and discussed how well the ad explanation described why that ad was presented to them. We continued this process until each participant had observed explanations from at least five different advertisers. Participants compared the explanations and stated which they preferred more, and why.

The Advertising Algorithm View

In the second view, we provided all participants with more information by showing them the interests and demographic features that the Facebook advertising algorithm inferred about them (Figure 1). We checked for users' prior awareness of this *Algorithm View*, and demonstrated this view to those who were unaware of it via the interviewer's Facebook account using Facebook's "Manage Your Ad Preferences" option. Next, participants explored their own actual Facebook Algorithm View, and talked about the algorithmically-inferred attributes they felt comfortable sharing. During this phase, we asked participants to discuss these attributes and how these attributes aligned with their identity. Although we term this the Algorithm View for this report, we did not use the word "algorithm" during any part of the study.

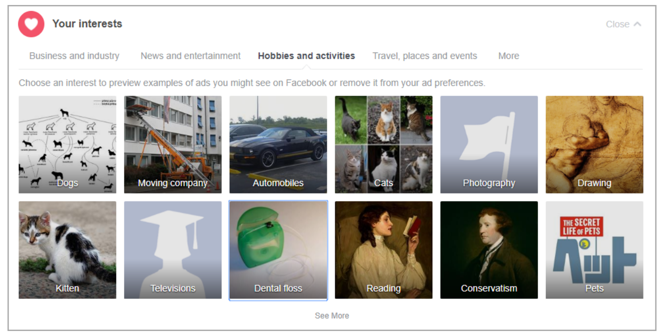


Figure 1. Algorithm View: This view shows the interests that the Facebook advertising algorithm infers about a user.

The Advertiser View

After discussing the Algorithm View, we demonstrated the Advertiser View, which discloses still more information to users. In this view, an advertiser can build a target audience based on demographics, interests, and behaviors via a variety of inferred attributes (see Figure 2).

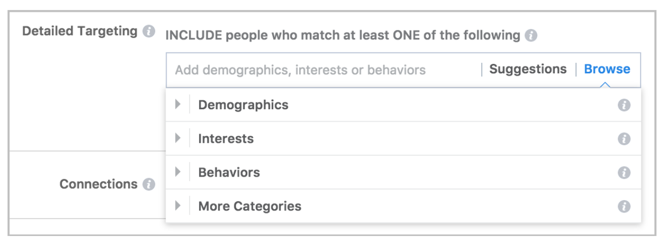


Figure 2. Advertiser View. This view shows the options given to an advertiser when creating an ad for Facebook.

We first asked participants to choose a product or service they were interested in and might purchase in the near future. Next, we asked them to use the Facebook Advertiser View to create a target audience consisting of users similar to themselves. At this point, many participants noticed that attributes from their Algorithm View appeared as target attributes in this Advertiser View. Participants were allowed to refer to anything in the previously shown Algorithm View.

A Speculative Design Task

To understand how participants would like advertisers to communicate the algorithmic process to users, we asked them to design an ad explanation for a product or service of interest to them. This design task was conducted two times: First after the participants viewed the Ad Explanation View and again after created a target audience using the Advertiser View. These tasks complemented each other. In the first speculative design task, participants were not yet aware of the "exact" factors used to target ads to them, while in the second, they were. We compared the explanations of these two tasks to see how awareness of exact targeted attributes was reflected in participants' desired ad explanations.

Writing an Explanation after the Ad Explanation View

After they viewed some of their own ads and explanations, participants chose another ad that they found interesting or relevant without looking at its explanation (if it had any) and guessed why the advertiser tailored this ad to them. Next, they wrote an explanation for this ad that they desired the advertiser to show. To minimize design fixation and maximize diversity, we provided participants with examples based on press reports [9, 23, 50] that were very different from previously viewed ad explanations (see Figure 3). We avoided explanations that listed obvious demographic categories (e.g., age) or behavior (e.g., you visited a page about X) because participants had already seen such explanations in the Ad Explanation View[1].

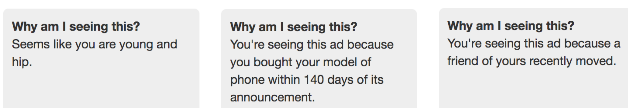


Figure 3. Examples: We gave participants diverse examples from trade press: a vague explanation (left), an explanation that stated something that the user was never asked to explicitly disclose (middle), and one that described a characteristic of the user's network (right).

Writing an Explanation after the Advertiser View

After targeting "people like themselves" in the Advertiser View phase, participants wrote an explanation from the perspective of an advertiser to provide the audience (people like them) with an explanation for why they were targeted. Participants were free to look at the Advertiser View and use any information in their ad explanation, including the features they just chose to target the ad. Participants were then told that the ad would appear on their own Facebook News Feed because they were a part of that audience. They then evaluated their ad explanation design from the perspective of a user, and described what they liked or did not like. To reiterate, note that we asked participants to target an audience as an advertiser, to write an ad explanation as an advertiser, but then we asked them to evaluate and revise it as a Facebook user. In pilot studies, we found that this ordering was necessary so that users were not confused about which role (advertiser or audience) they were playing during a specific task.

Participants

This is a small-sample laboratory study, yet it was still imperative to avoid a convenience sample of computing students or professionals with insider perspectives about social media platforms and algorithmic processes. We therefore used craigslist to recruit participants from San Francisco, California and the surrounding area. We requested participants with Facebook accounts who could bring their own personal device. From the 207 replies we received, we performed non-probability modified quota sampling to balance five characteristics with the proportions of the US population: gender, age, education, race/ethnicity and socioeconomic status. We recruited 32 participants with various occupations such as hair stylist, driver, mechanic, etc. The participants in our sample were 50% women and were 18 to 64 years old: 18-24 (12.5%), 25-34 (37.5%), 35-44 (19%), 45-54 (28%), and 55-65 (3%). The sample consisted of Caucasian (47%), Asian (16%), African-American (12%), Hispanic (6%) participants. The rest (19%) were multiracial. 44% of the participants had an income of less than \$50,000, 43% between \$50,000 - \$150,000, and 13% greater than \$150,000. Participants had reached varying levels of education: high school graduates (3%), some college experience (34%), Associate's degree (9%), Bachelor's degree (38%), and Master's degree or above (16%). Participants received \$60 for their participation.

Data Analysis

To discover and organize the main themes discussed by participants, one researcher first conducted line-by-line open coding and labeled preliminary codes for each interview. Next, the researcher used axial coding to extract the relationships and similarities between themes to group them into categories. We used Nvivo [35]—a qualitative data analysis tool— to map all interviewees' statements to our categories and subcategories. Three researchers then conducted face-to-face meetings to discuss and revise the extracted themes for agreement.

WHY AM I SEEING THIS AD? (RQ1)

We found that only five of the participants were aware of the existence of ad explanations: "*Sometimes there's a little text. It's like 'why am I seeing this?,' and it tells you, 'based on your certain interests, we thought this would be applicable to you.' [...] It was just interesting information. It was like, 'oh, cool.'* " (P13). The rest had never seen an ad explanation and they "*don't think the ad's going to tell me how it was being tailored to me*" (P18) or vaguely remembered an ad disclosure icon but "*never clicked on it*" (P10). However, they were still "*curious of why and how that happens*" (P25). Some (n=8) became surprised when they saw an ad explanation during the study as they did not expect that an advertiser would reveal such information: "*That seems fairly transparent and nice, and it's weird because I didn't even know it was there [chuckle]*" (P6).

When participants compared the actual ad explanations that they saw, participants' reactions varied based on the 1) interpretability, 2) "creepiness", and 3) linkage to identity of the ad explanations. These factors were also reflected in the ad explanations participants designed later in the study.

Interpretability

Many advertisers used vague and simplistic language in their ad explanations, making it difficult for users to understand why they were seeing an ad. For example, Figure 4(a) states that

[1] In our pilot studies, this speculative design task was given prior to viewing existing ad explanations to minimize fixation. However, we found that many participants had never seen an ad explanation before, and therefore had trouble writing one. Therefore, we moved this task after the Ad Explanation View.

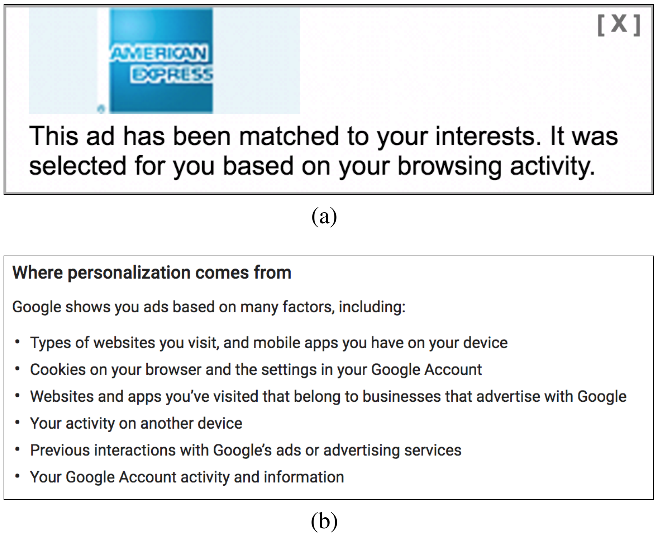


Figure 4. Two uninterpretable explanations. Both lack specificity about what activity or interest has resulted in a user being targeted for this ad. Although (b) is more detailed than (a), the lack of specificity made it still uninterpretable.

an ad has been targeted to a user based on interests inferred from the user's browsing activity. This explanation, however, does not describe what those interests were or any specific browsing activities. Many participants (n=20) were confused by the ambiguity of these explanations. For example, P3 stated that these explanations "*seem like a black box.*" A lack of explicit connection between the ad explanation and the ad made the explanation unsatisfactory and uninterpretable: "*This just tells you how they do it for every ad, it doesn't tell you why it's that specific ad*" (P13).

Some advertisers tried to elaborate the types of browsing activity they used to target ads to users (see Figure 4(b)). However, participants rejected those statements that did not match a particular activity to a particular ad by arguing that these did not count as explanations: "*That's pretty broad, just saying 'search history, other devices or cookies,' without saying what specific searches I did make*" (P14). Furthermore, unspecific statements prompted users to express uncertainty: "*This doesn't say anything specific; so I don't know what information they're looking at*" (P3). They argued that these explanations "*had a lot of text but really just said nothing specific*" (P14). Using this standard, participants identified the majority of advertiser statements as not really being explanations. Even advertiser statements that included information new to the participants were viewed negatively if this information was about how ad targeting worked in general and not about a specific ad.

Interpretable Explanations

A minority of advertiser statements were interpretable–they provided specific information about the data or the inferences an advertising algorithm used to target a particular ad to a user. Figure 5(a) shows an example which explains that an ad has been targeted due to a user's visit to a specific website, age range, and location. Most participants (n=22) preferred such explanations because these explanations were more interpretable: "*I guess I'm more comfortable with it because I understand it better. The other ones, I don't understand what they're doing*" (P5).

Trustworthiness

Some participants (n=6) felt that advertisers were intentionally vague in their ad explanations, resulting in a lack of trust: "*The[se] ones seem vague, almost on purpose, and I don't necessarily trust the way they gather their data*" (P5). They wanted a "*more transparent and specific [explanation], because, excuse my language but these [explanations] are like bullshit*" (P31). Participants stated that they would trust advertisers who provided interpretable and specific ad explanations more: '*I would trust [advertiser's name] more, it[s explanation] is simple, it's easy to read, and it tells you the reason*" (P7). This finding recalls previous work that showed an oversimplified explanation of how intelligent agents work can cause users to lose trust in the system [30].

Completeness

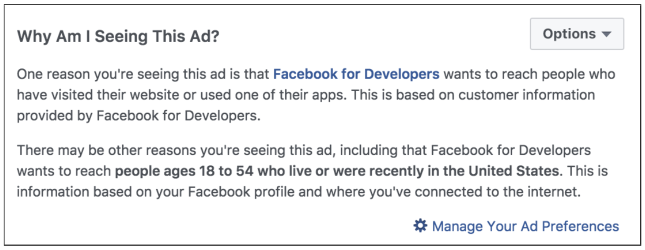
Some interpretable explanations did not describe why an ad was tailored to a user in exact detail, but still satisfied users. For example, Figure 5(b) shows an explanation that participants found positive and interpretable. It stated that the user's inferred interest in personal finance, age range, and location resulted in this targeted ad. This explanation, however, did not specify the exact pages the user liked or the ads she clicked. To understand if users wanted this kind of completeness, we asked them if they desired more specific details about what was left unspecified in this type of ad explanation. Participants, however, stated that "*that's more than enough*" (P19) for them. They said that such an explanation identifying factors but not their values still "*covers everything, it's short and sweet, and simple*" (P20) and it "*didn't leave room for me to ask a lot of, like too many more questions*" (P17). Discovering precisely what makes an ad explanation satisfying, interpretable, and complete even though some information is omitted remains an open question for future work.

Designing an Ad Explanation

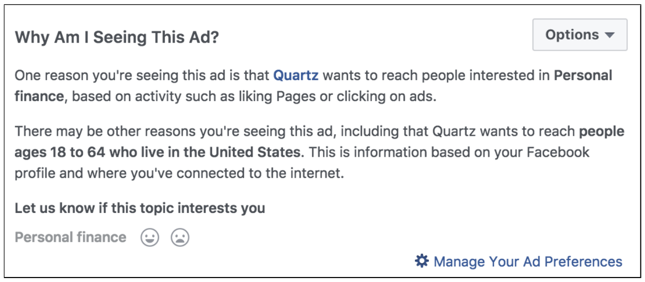
Participants also enacted their definitions of interpretability when they wrote their own ad explanations. They tried to write more detailed explanations and described these as "*easier to understand* " (P7). Participants invoked advertiser motives by referencing honesty: "*the honest reason why they are showing this ad is what I wanna see.*" (P8). One example of a participant-generated ad explanation stated that: "*You are seeing this ad because your frequent browsing history shows an interest in animals, specifically dogs. Data also shows that you frequently purchase these items and we have provided suggestions for future purchases*" (P4). Participants contrasted the explanation that they wrote with the ones provided by advertisers by saying that their designed explanations contained "*more [specific] information versus generalized*" (P25) information.

"Creepiness"

Sometimes, participants identified ad explanations as "creepy." Both vague, uninterpretable statements and specific, interpretable explanations could be labeled as creepy. Participants (n=7) stated that vague and uninterpretable explanations (such



(a)



(b)

Figure 5. Two interpretable ad explanations. Both provide information about the data and inferences used to target this ad. However, (b) is not as complete as (a) because it does not show the exact pages the user liked or the ads the user clicked on.

as Figure 4(a) and Figure 4(b)) were creepy because they reminded them of "*big brother of advertising*" (P31) that "*sounds really invasive*" (P28). Some participants' belief that advertisers go through their private emails or even phone conversations to target ads were reinforced by unspecific explanations: "*I feel like definitely [they looked at] my email still and they're not saying that [...] they're afraid of people complaining that you've been in my email*" (P28).

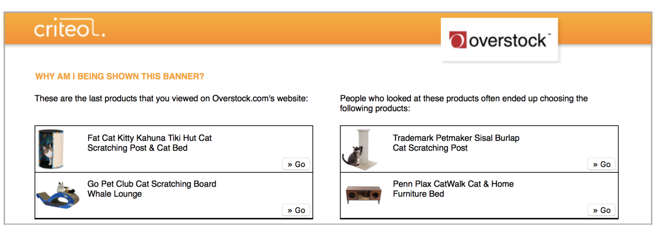


Figure 6. A creepy ad explanation. While this explanation is interpretable for users, pointing to the exact products/services the user visited made it creepy for some users.

We found some interpretable ad explanations, which specifically explained why an ad was targeted, could also be creepy. Figure 6 shows an example of an interpretable but creepy explanation. Ad explanations that pointed to exact products/services the user visited were creepy for some participants (n=4):"*ohhh, that's kind of creepy [...] that it keeps track of the exact products I was looking at*" (P6). In another example, P19 freaked out when she received an ad because she had close friends with a birthday between seven to 30 days from now: "*How would they know my friends' birthday? This is exactly why my sister does not have Facebook, Snapchat, Instagram, and etc. and says 'Get off that[sic] crappy sites. They're getting all your information.'* " Some specific explanations also signaled the exchange of data between advertisers, which turned out to be creepy as well: "*This makes me feel like Amazon sold my information to Facebook*" (P4).

Designing an Ad Explanation

In the speculative design tasks, some participants (n=6) preferred to omit some specifics about the ad targeting process in order to avoid being creepy.

For example, in the first speculative design task, P16 stated that he received a Samsung Galaxy S8 phone ad because "*I'm loyal to this brand. I've had an S2, 3, 4, 5 and 6.*" However, his ad explanation—"*Because you've made previous purchases for this brand numerous times in the past, and you're loyal to this brand*" (P16)—did not mention the exact purchases because he thought "*that might become scary*": " '*On November 5th, 2016, you bought this phone. Don't you think you need a new one?' I don't think I like that. I know they probably know that and everything else, but no, I'm good with that. [Otherwise,] that'll start scaring me.*" But participants at this stage of the study, could only speculate about why they were seeing an ad. Did they omit detail from a fear of being inaccurate?

After participants were shown more information about the factors used to target ads they returned to perform a second speculative design task. This time, participants were aware of the exact reasons an ad might be targeted to them because they selected the targeting factors themselves. We found that although participants were now aware of the reasons for targeting an ad, they still left out details that they felt were creepy.

For example, in the second speculative design task, P5 wrote an explanation for an ad (targeted to himself) by identifying an audience that was young, interested in music, had a specific range of income, and were home renters. However, he only included the first two features in his desired explanation because, even though the advertiser might know his income or his homeownership status, "*I don't [want the advertiser to] tell it back to me [laughing]*" because "*I don't want to know that they know that information*" (P27). To underscore the context here: Participants were aware of all the variables used in ad tailoring, but some wished that they weren't aware. There were features of the advertising system that they would rather not have learned or be reminded about.

Overall, users tried to write a "*more transparent*" (P31) explanation but avoided sensitive topics and were sometimes keenly aware of the tone of their writing. They wanted transparency "*without being creepy and being like I kept track of the last five dresses that you've purchased*" (P6).

"Linkage" to Identity

We found that linking an ad explanation to the user's identity correlated with users' satisfaction. Participants (n=24) expressed a negative view of explanations for personalized ads that they felt were not personalized enough. They argued that a "*weak linkage*" (P22) between an ad and the user's identity in an ad explanation illustrated that advertisers "*take an impersonal approach to explaining something like a personal ad, which is kind of contradictory*" (P17). This was regardless of the explanation's interpretability or specificity. For example, P15 described that he did not like a specific ad explanation because "*they didn't really feel like they were directed to [him]*" (P15). Therefore, participants did not like an ad explanation if it did not feel "*personal*" (P17) enough: "*Because my friend is looking for fashion, Chanel bag, they think that I might be interested? That, to me, is mumbo jumbo*" (P19).

On the other hand, when an ad explanation showed a link to their identity, participants thought the advertiser was "*kind of going an extra mile*" (P29) to make the ad "*geared more towards*" (P20) them. As P11 described, these explanations "*gave me insights into 'why me' more specifically. It said my demographic, and then it said the reason.*" This made participants more satisfied with their ad explanation "*because I like to see how I'm categorized*" (P29). On the other hand, when participants did not see the link to their identity, although the ad sounded targeted to them, a few stated that they did not "*think this is the real reason for this particular ad*" (P12) and "*there's got to be more to it [...] they're lying*" (P31).

Designing an Ad Explanation

The preference for a link to identity was also demonstrated when participants designed their desired ad explanations. Participants (n=17) argued that their explanations should be "*detailing it towards of you as an individual*" (P32): "*I would like to hear I'm seeing the ad because I'm their target, the product is [...] designed for me, it's not because I just saw it*" (P7). They, therefore, wrote explanations that referred to the interests that defined an important part of their identity: "*because music is my passion, all I had to see is 'you've visited music sites' [...] it'd be funny if it said something like 'do you have any other interests besides music, [P8's name]?'* " (P8).

Participants also preferred to include the attributes they were proud of. P2, for example, selected both "people between ages 20-30" and "millennial" as her target audience, but when she wrote an ad explanation, she chose to include the "millennial" option "*because there's some pride in being a 'millennial,' opposed to 'between ages 20-30'* " (P2). Participants wanted their ad explanations to tell them that they were a select audience, like in P14's designed ad explanation for a Santa Cruz mountain bike: "*Because you like the same cool things we do (bikes, beer, coffee, Santa Cruz)*". P14 even asked to "*have something written out that it would seem like it was written by a person instead of just like a copied form with all the tags.*" This shows the importance of the user being recognized for their identity and "*not just because I'm a warm body*" (P15).

To Whom Does an Ad Explanation Matter?

While a well-designed ad explanation can increase user satisfaction with their ad experience, it is not equally important to all users. From our interviews, we found that the importance of ad explanations depends on how much a user is 1) interested in online ads and 2) concerned about privacy.

Prior Interest in (Personalized) Ads

During the pre-interview, we evaluated participants' existing interest in and interactions with online advertising. We surfaced three categories of interests in online ads: Participants found an ad "rarely" (n=8), "sometimes" (n=19) or "often" (n=5) useful. Participants who found advertising useful said that they preferred tailored advertising to generic advertising because the usefulness of an ad "*depends on how relevant it is*" (P12). They argued that personalized ads sometimes helped them get what they were looking for or saved them money: "*I was planning to join [a] Zumba training program [...] I looked it up before but I didn't book it, and then I saw the ads. They had 20% off, so I booked it*" (P7).

We found that those who "often" or "rarely" found online ads useful did not care about ad explanations much because the former liked all ads while the latter would not look at ads anyway. Those who "often" liked advertising stated that they "*just didn't care*" (P10) to click on an ad explanation because "*to tell you the truth, I would never even need to look for the reason. I mean it's interesting to know why but I don't even really care because if this is a product that I'm interested in, I'm gonna stop and look at it, if it's not, all I'm gonna do [is to pass]*" (P8). Those who "rarely" found an ad useful stated that they "*couldn't think of a reason that [an ad explanation] would make [them] feel better about [an ad]*" (P5) because they already did not like the ad.

On the other hand, those participants who found online ads "sometimes" useful stated that an explanation was very informative: "*It's a very impressive thing, you really taught me a lot about [ads]. I had no idea that that's how things work*" (P15). If an ad had a clear explanation, participants stated that they "*appreciate that type of ad because [...] the [advertisers] are transparent about where they got your information from*" (P28). It is possible that interpretable ad explanations can result in a more informed and trustworthy ad experience for those users who do not have extreme feelings (positive or negative) about online advertising. In our study, more than half of the participants fell in this group (n=19).

Prior Concerns About Privacy

While perceived as more useful than generic ads, tailored ads brought privacy concerns. In the pre-interview we asked participants about privacy and distinguished 1) people who were not worried (n=23) and 2) people who were worried (n=9) about advertisers using their data for the purpose of ad tailoring. Those who were not worried about their privacy stated that they "*understand that with using the Internet, data is being collected by every site—cookies and all that shit*" (P13). Some even said that "*there's no privacy anywhere*" (P16) and "*the genie's out of the bottle*" (P10), and they had "*kind of come to terms with that*" (P29). However, those who were worried about their privacy called tailored advertising "*an intrusion of your own privacy*" (P25)

Ad explanations mattered the most to participants who did not like advertising, mainly due to privacy concerns. They asserted that "*it's better that [an explanation] is here than it's not*" (P30). Participants said they might be more willing to interact with an ad when an advertiser provides them with an honest reason: "*So after this experience, I will even say probably I will start clicking on those things more just out of curiosity, just to see what they say, and potentially, if I see some advertisers that are more transparent, [...] I appreciate that about their company, [and] I probably will be more likely to buy from them*" (P31). Communicating the ad curation process to users who are worried about their privacy may increase their trust in an advertiser.

IN THE EYE OF THE ALGORITHM (RQ2)

None of our participants had ever seen the Algorithm View. They believed that they "*can't get that much information about data collected about*" (P30) them. Participants, however, were quite interested in seeing such a view and were even willing to pay for it: "*If I could buy my internet profile somewhere and learn about, see what the internet thinks I am, I would totally do that [chuckle]. I think it's really interesting [to see how] I've been categorized, what they think of me, and ads [for me]*" (P29).

The Algorithmic Self

"It's the best version of your own movie." (P12)

Observing their algorithmically-inferred attributes, the *algorithmic self* [6], made participants argue that advertisers utilize "*much more of what you do, and using that to target and to generate ads [...] versus just what you say*" (P12). Participants stated that their algorithmic self reflects that "*how many algorithms and things actually go into social networking websites, and there's more math and science involved [...] , 'Okay, I can see the data collection and how they actually make it come to life'* " (P17). They, however, argued that "*your life that you portray on Facebook isn't probably the most accurate reality, it's the best version of your own movie*" (P12).

Algorithmic Self, Real Self, and Ideal Self

Comparing their algorithmic self with their self-described attributes, which participants felt was their *real self*, some people (n=10) expressed great satisfaction when the algorithm detected attributes that they were proud of: " *'very liberal', nice, glad it knows that [chuckle]*" (P5) or "*Oh, it calls me a frequent traveler [chuckle]*" (P11). This satisfaction turned to great dissatisfaction if the algorithm detected attributes that were opposite of those participants were proud of. For example, P16 was angry when the algorithm called him a "late technology adopter" while he was proud to identify himself as an "early technology adopter": "*I don't know what the hell this is all about. [...] We have all the newest crap [...] Every time the new phone comes out, we get them. [...] We have all the video game systems, Smart TV, Roku, Wii.*"

Participants were happy to be assigned attributes by advertising systems that were wrong but flattering. When an algorithmically-inferred interest described an attribute a participant did not have but would be proud to possess (the *ideal self*) the participant was still satisfied. For example, a 30-year old participant who was mistakenly described as a "baby boomer" by the algorithm said that her behavior (that she was proud of) might cause this mistake: "*Maybe they think I'm a business-oriented woman, maybe that means I tend to be an older woman, or more mature woman rather than looking ads for Botox, or Kim Kardashian or Taylor Swift*" (P28). Similar to the trend we observed in RQ1, these statements reflect the importance of recognizing users' identity when communicating the algorithmic process in behavioral advertising.

Assuming Algorithmic Authority

"People are firm believers in free will. But they choose their politics, their dress, their manners, **their very identity**, from a menu they had no hand in writing. They are constrained by forces they do not understand and are not even conscious of."

Friedman,1999, p240 [17]

Before walking through the Algorithm View, several participants (n=12) illustrated a strong belief in algorithmic authority, arguing that advertising algorithms "*seem to really understand what your interests are, their robots know me, the programs that they wrote, they know about me*" (P9). Participants said that they "*always assume that [advertisers] have that technology to target*" (P29) the right audience. This perception corresponds with the "eye of providence" folk theory from previous research wherein users perceived algorithmic systems to be all-powerful and all-knowing [13, 49].

Justifying Algorithmic Decisions

While many algorithmically-inferred interests matched participants' real-selves, there were many interests that did not. When participants started viewing these incorrect interests, rather than stating that the algorithm was wrong, many (n=23) tried to find reasons to justify those mistakes. This effort partly arose from the fact that we, as humans, tend to find patterns (even in randomness) and fit explanations to unknown phenomena (here incorrect algorithmic outputs). This tendency of explanation, however, becomes stronger for those users who believe that an algorithm could not be incorrect. For example, Springer et. al. [48] showed that even when an algorithm functions at random, users still try to justify a wrong algorithmic decision due to their belief in algorithmic authority.

In our study, we observed a similar trend where users who assumed algorithmic authority tried to justify incorrect algorithmic decisions. For example, P8 did not know why the algorithm inferred an interest in "Minneapolis" for him. He, however, tried to come up with an explanation by making a connection between what he really liked and what the algorithm inferred: "*Minneapolis, I'm not sure why that's there. Maybe because I have an interest in Prince and he was in the Minneapolis area. The musician Prince.*" Another participant who had an interest in "Whole Foods" but didn't know why guessed: " *I think Amazon just bought Whole Foods, so maybe that's why [...] because I do buy stuff from Amazon*" (P16). Even if participants could not think of a concrete reason to justify an incorrect interest, many (n=14) still argued that they must have done an action that "*connected something with [that interest]*" (P20): "*I don't know what I am politically, but I bet you my user browsing is liberal for sure*" (P11). A few participants started reviewing their Facebook account (their likes, groups, etc.) to justify their incorrectly inferred interests, rather than believing that the algorithm could be wrong.

Taking the Blame: When partitioning the responsibility of a mistake between the algorithm and themselves, some participants (n=7) even put the responsibility on themselves rather than the algorithm. These participants believed that they did not provide the algorithm with the right input data. For example, P11 said that he "*'unliked' every single page [on*

Facebook] until [he] didn't 'like' anything" and that's why his algorithmic self only included a few interests. In addition, P8 stated that one of his important interests was not detected because "*a lot of what I do is based on another apps [...] maybe [Facebook is] not getting the information [...]. I should follow them in Facebook [...] I gotta help [Facebook] out*".

Our results support previous findings in the realm of personality judgments [55] when users were hesitant to argue against what an algorithm inferred about their personality, even though they disagreed with it. This could be because users felt unqualified to oppose an algorithmic decision, even if it was about their own personality. These results show the necessity for redesigning algorithmic systems to increase user algorithmic literacy and reduce the assumption of algorithmic authority.

A Path to Algorithm Disillusionment

> From "*Their robots know me*" to "*Maybe you are not as smart as I thought you were*" (P9)

While many participants justified incorrect algorithmic decisions at the beginning of the study because of their strong belief in algorithmic authority, observing more and more incorrectly inferred interests through the course of the study gradually led many (n=26) to *algorithm disillusionment*: the realization that advertising algorithms were not as perceptive and powerful as users thought.

Questioning the Algorithmic Self

As participants (n=21) noticed more and more discrepancies between their algorithmic self and their real self, they started to confront their algorithmic self. P25, for example, argued that "*they must think I'm a boozy person on the internet. [...] I do drink wine, but [...] I'm not an alcoholic. This is not a good representation of me.*" Some said that their algorithmic self was "*not very telling*" (P29) because they were "*way more cultured than this, actually, all this stuff is kind of silly, not really deep stuff [chuckle]*" (P11). Other participants received incomprehensible interests such as "tears", "Wednesdays", or "toxicity". This led many participants to question algorithmic authority because the algorithms are "*surprisingly not very good [even though] they access so much data*" (P6).

Some participants (n=12) were also disillusioned when their algorithmic self did not include interests that were obvious or important: "*I'm surprised it didn't get my undergrad institution*" (P2). Participants usually believed they had already provided the algorithm with enough input data to infer those interests: "*I was going to say, photography is a huge interest for me. Why that's not showing up? Because I post a lot of photos on Facebook. I take photography classes on Lynda.com. I read photography websites, blogs, magazines* (P9).

Diagnosing Algorithmic Weaknesses

While participants tried to find out why their algorithmic and real selves were misaligned, many (n=16) discovered some common (and sometimes funny) mistakes that advertising algorithms made: *'Kayaking,' I can't figure out where this is. Okay, oh wait. This is weird. I was wondering why. I have the app 'Kayak'. Kayak is this travel comparison site, not a sport of kayaking in the water thing [laughing]*" (P12). Because of these mistakes, participants thought that advertising algorithms might make assumptions such as "*'well if you like this, then you like that,' and it seems a little bit of a stretch*" (P12). Participants did "*not like that [advertisers] simplify people that much into these weird little categories [chuckle]*" (P6). They argued that advertising algorithms are "*making a lot of assumptions that are overly specific in these things [...] It's putting someone into categories, but maybe someone isn't defined by a category*" (P15).

While many participants began the study with beliefs like "*their robots know me,*" being exposed to the sometimes large misalignment between algorithmic and real selves and discovering algorithmic errors made participants realize that "*Ah, maybe you are not as smart as I thought you were [laughing]*" (P9). We argue that this disillusionment could be effective in building a more realistic and intelligent interaction between users and algorithmic systems. We elaborate on the design implications of disillusionment in the discussion section.

LIMITATIONS

This was a qualitative project involving a non-probability sample. Many choices in the research design favored gathering diverse and even speculative data to reveal the breadth of possible user reactions and provide a basis for further work. Further research is needed to generalize these results.

This study was not longitudinal. Except for the design tasks, many of our methods focused on opinions and attitudes rather than behavior. For example, we described some results (such as algorithm disillusionment) as attitude change occurring over the course of the study. Yet if this phenomenon is replicated it will be important to determine how persistent it is over time and whether it translates into changes in user behavior.

DESIGNING FOR DISCLOSURE

The Requirement for a Critical Stance

In this paper, we studied user reactions to ad explanations and found that participants preferred interpretable, non-creepy ad explanations that have a recognizable link to their identity. User satisfaction, however, is only one goal of algorithmic transparency. A satisfying explanation might be misleading or even completely false. Deceptive business practices are prohibited by law, while targeting certain kinds of advertisements using certain protected categories is illegal (for example, in the US see [7, 8]). Ideally, algorithmic transparency would provide the user with the information required to protect her own privacy while also providing interested third parties (like consumer advocacy groups and government regulators) the ability to identify undesirable behavior by an algorithmic system.

User studies like this one have no way to understand if an ad explanation actually reveals all of the data and inferences an advertising algorithm used to target an ad, or if the descriptions of the algorithmic processes at work are defensible. This study and future work on users should be complemented by algorithm audit techniques [43]. For example, [2] used controlled experiments to compare what private data or inferences advertising algorithms use to target ads to users and how much of that information an ad explanation reveals.

Designing to Convey Algorithm Limitations

Many online users believe in algorithmic omniscience. They believe that AI and algorithms could control or destroy the world, and this scares them sometimes [36]. This belief has resulted in misperceptions about algorithmic systems. For example, people believe that advertising algorithms collect more data about users than they actually do [53]. Users also fear algorithmic systems because they do not know how their information is processed by these systems. As described in [22], when Facebook recommended a previously-unknown great-aunt, this scared the user because the process that resulted in such an intimate connection was so unclear.

Our findings show that this fear often subsided when people observed that algorithms were not infallible. Participants became disillusioned, but also became more secure in the realization that algorithms were limited in their power. Conveying or communicating these limitations as users interact with opaque systems may put users at ease. But how do we do this?

The first step in conveying algorithm limitations into online behavioral advertising is to increase the visibility of users' algorithmic self. While a few advertisers such as Facebook and Google provide the Algorithm View to users, usually such views are buried within the system interface (and typically reveal only a small proportion of the users' stored information). Recall that none of the participants in our study were aware of or had seen this view. One option to increase this view's visibility is to add more clues in the main interface of the system. For example, P11 suggested that Facebook could provide users with their algorithmic self occasionally in their feed, similar to what Facebook does for Facebook memories: "*Facebook does do that thing at the end of the year, like 'your eight year anniversary on Facebook. In those years, you've liked ...' But I've never seen one super specific [view] on my likes and dislikes [...] that's kind of what that reminds me of [...] It would be really cool*" (P11).

Some participants wanted to increase the visibility of this view by showing it to their friends. For example, when P17 explored the Algorithm view, he said: "*I gotta have to show people.*" In another example, P11 suggested a "share" option for the Algorithm View: "*this is cool, I like this. It'd be cool if I could share this with my friends, and they'd probably think it was cool, too.*" These suggestions would allow for engagement and experimentation with opaque algorithmic systems. Finding algorithm disillusionment via such interfaces offers knowledge and comfort.

Designing for Algorithm Engagement

While users benefit from the right level of disclosure about why an ad is tailored to them, currently, the icons to access ad explanations are usually buried or hardly visible in the interface—only five participants in our study had ever interacted with these explanations. Previous work has also shown the failure of the current ad disclosure mechanisms in communicating the algorithmic process [31]. Another reason for this failure is users' reluctance to click on these icons because "*how many times am I going to click on that? So it's also a waste of time*" (P11). Some also argued that they "*don't trust [advertisers] enough to even do anything via these AdChoices. It was just another like pseudo engagement that they were getting out of [the ad].*" So, with these challenges, how can ad designers provide users with more engaging ad explanations?

When the Explanation Becomes a Part of the Ad

One solution, as P25 suggested, could be to add an explanation as the fine print to the ad itself because "*I don't think that you should have to go out of your way to click on 'why am I seeing this ad.' Rather than you having to go out of your way to search why, why don't they just tell you why directly*?". However, an ad explanation could be too long to fit without dominating the ad and distracting the user. Another option is to show only the reason with a recognizable link to the user's identity and offer a "more" option if the user was interested in more detail.

When the Explanation Becomes the Ad

Rather than having an ad explanation in fine print, the ad explanation could become an integral or central focus of the ad. We saw this when some participants (n=11) designed their own ad explanations and started "*writing it like an ad*"(P5). Their ad explanations became the motivation for purchasing that product/service. For example, P6, wrote: "*Because you're interested in fashion trends, here is the latest summer dress collection from French Connection. Read more about it on their website.*" Via these explanations, "*why I'm seeing [an ad] would become like the ad*" (P31).

Such designs could not only help users understand why they saw an ad easily, but it might also engage them with the ad if the ad includes a recognizable link to a part of their identity. For example, if an ad is targeted to a "frequent traveler," rather than having the reason in fine print on the ad, the main ad message could read "visit our travel website because you travel frequently." We believe, if designed carefully, such ads could also gradually increase users' trust and preference in their personalized ads; as P31 said, "*transparency could actually be helpful as a marketing tool.*" However, evaluating such designs remains for future work.

CONCLUSION

In this study, we contribute to understanding how communicating aspects of the algorithmic ad curation process affects users' perception of their ad experience. Our analysis highlighted misperceptions about algorithmic omniscience which subsided when users were exposed to the inner workings of the system. This illustrates that as more ads are tailored to users via algorithmic processes, advertisers should provide users with interpretable explanations about these processes. Advertisers also need to increase the visibility of such disclosure mechanisms as the current practices fail to do so. Communicating algorithmic processes not only benefits users by providing them with a more realistic understanding of how their information is processed, but could also help advertisers to regain or increase user trust in and satisfaction with their ad experience.

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REFERENCES

1. Jagdish Prasad Achara, Javier Parra-Arnau, and Claude Castelluccia. 2016. Mytrackingchoices: Pacifying the ad-block war by enforcing user privacy preferences. *arXiv preprint arXiv:1604.04495* (2016).

2. Athanasios Andreou, Giridhari Venkatadri, Oana Goga, Krishna P Gummadi, Patrick Loiseau, and Alan Mislove. 2018. Investigating Ad Transparency Mechanisms in Social Media: A Case Study of Facebook's Explanations. In *The Network and Distributed System Security Symposium (NDSS)*.

3. Julio Angulo, Simone Fischer-Hübner, Tobias Pulls, and Erik Wästlund. 2015. Usable transparency with the data track: a tool for visualizing data disclosures. In *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems*. ACM, 1803–1808.

4. Howard Beales. 2010. The value of behavioral targeting. *Network Advertising Initiative* 1 (2010).

5. Matthew Chalmers and Ian MacColl. 2003. Seamful and seamless design in ubiquitous computing. In *Workshop at the crossroads: The interaction of HCI and systems issues in UbiComp*, Vol. 8.

6. John Cheney-Lippold. 2011. A new algorithmic identity: Soft biopolitics and the modulation of control. *Theory, Culture & Society* 28, 6 (2011), 164–181.

7. Federal Trade Commision. 2011. Facebook Settles FTC Charges That It Deceived Consumers By Failing To Keep Privacy Promises. (2011). http://bit.ly/1U44BfY.

8. U.S. Equal Employment Opportunity Commission. retrieved on Dec 2017. U.S. Equal Employment Opportunity Commission: Discrimination by Type. (retrieved on Dec 2017). https://www.eeoc.gov/laws/types/.

9. Connectio. 2015. 25 Weirdly Specific Facebook Ads Targeting Ideas You Didn't Know Existed. (2015). http://connectio.io/25-facebook-ads-targeting-ideas/.

10. Matthew Crain. 2016. The limits of transparency: Data brokers and commodification. *new media & society* (2016).

11. Nicholas Diakopoulos. 2014. Algorithmic-Accountability: the investigation of Black Boxes. *Tow Center for Digital Journalism* (2014).

12. Nicholas Diakopoulos and Michael Koliska. 2017. Algorithmic transparency in the news media. *Digital Journalism* 5, 7 (2017), 809–828.

13. Motahhare Eslami, Karrie Karahalios, Christian Sandvig, Kristen Vaccaro, Aimee Rickman, Kevin Hamilton, and Alex Kirlik. 2016. First I "like" it, then I hide it: Folk Theories of Social Feeds. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. ACM, 2371–2382.

14. Motahhare Eslami, Aimee Rickman, Kristen Vaccaro, Amirhossein Aleyasen, Andy Vuong, Karrie Karahalios, Kevin Hamilton, and Christian Sandvig. 2015. I always assumed that I wasn't really that close to [her]: Reasoning about Invisible Algorithms in News Feeds. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. ACM, 153–162.

15. Motahhare Eslami, Kristen Vaccaro, Karrie Karahalios, and Kevin Hamilton. 2017. "Be Careful; Things Can Be Worse than They Appear": Understanding Biased Algorithms and Users' Behavior Around Them in Rating Platforms.. In *ICWSM*. 62–71.

16. The Office for Creative Research. 2013. Behind the Banner: A visualization of the adtech ecosystem. (2013). http://o-c-r.org/behindthebanner/.

17. Lawrence M. Friedman. 1999. *The Horizontal Society*. New Haven, CT: Yale University Press.

18. Gerhard Friedrich and Markus Zanker. 2011. A taxonomy for generating explanations in recommender systems. *AI Magazine* 32, 3 (2011), 90–98.

19. Tarleton Gillespie. 2014. The relevance of algorithms. *Media technologies: Essays on communication, materiality, and society* 167 (2014).

20. Bryce Goodman and Seth Flaxman. 2016. EU regulations on algorithmic decision-making and a right to explanation. In *ICML Workshop on Human Interpretability in Machine Learning*.

21. Jonathan L Herlocker, Joseph A Konstan, and John Riedl. 2000. Explaining collaborative filtering recommendations. In *Proceedings of the 2000 ACM conference on Computer supported cooperative work*. ACM, 241–250.

22. Kashmir Hill. 2017. Facebook Figured Out My Family Secrets, And It Won't Tell Me How. (2017). http://bit.ly/2xjBorJ.

23. Facebook Inc. 2016. How Facebook decide for a person is Technology Early Adopter or not? (2016). https://www.facebook.com/business/help/community/question/?id=10153713741703882.

24. Facebook Inc. Retrieved on Dec 2017a. What are my ad preferences and how can I adjust them? (Retrieved on Dec 2017). https://www.facebook.com/help/247395082112892.

25. Google Inc. Retrieved on Dec 2017b. About Ads Settings. (Retrieved on Dec 2017). https://support.google.com/ads/answer/2662856?hl=en&ref_topic=7048998.

26. Farnaz Jahanbakhsh, Wai-Tat Fu, Karrie Karahalios, Darko Marinov, and Brian Bailey. 2017. You Want Me to Work with Who?: Stakeholder Perceptions of Automated Team Formation in Project-based Courses. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. ACM, 3201–3212.

27. Terry Parris Jr. Julia Angwin and Surya Mattu. 2016. BREAKING THE BLACK BOX: What Facebook Knows About You. (2016). https://www.propublica.org/article/breaking-the-black-box-what-facebook-knows-about-you.

28. Vera Khovanskaya, Maria Bezaitis, and Phobe Sengers. 2016. The case of the strangerationist: Re-interpreting critical technical practice. In *Proceedings of the 2016 ACM Conference on Designing Interactive Systems*. ACM, 134–145.

29. René F Kizilcec. 2016. How much information?: Effects of transparency on trust in an algorithmic interface. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. ACM, 2390–2395.

30. Todd Kulesza, Simone Stumpf, Margaret Burnett, Sherry Yang, Irwin Kwan, and Weng-Keen Wong. 2013. Too much, too little, or just right? Ways explanations impact end users' mental models. In *Visual Languages and Human-Centric Computing (VL/HCC), 2013 IEEE Symposium on*. IEEE, 3–10.

31. Pedro Giovanni Leon, Justin Cranshaw, Lorrie Faith Cranor, Jim Graves, Manoj Hastak, Blase Ur, and Guzi Xu. 2012. What do online behavioral advertising privacy disclosures communicate to users?. In *Proceedings of the 2012 ACM workshop on Privacy in the electronic society*. ACM, 19–30.

32. Bin Liu, Anmol Sheth, Udi Weinsberg, Jaideep Chandrashekar, and Ramesh Govindan. 2013. AdReveal: improving transparency into online targeted advertising. In *Proceedings of the 12th ACM Workshop on Hot Topics in Networks*. ACM, 12.

33. Christopher T Marsden. 2011. *Internet co-regulation: European law, regulatory governance and legitimacy in cyberspace*. Cambridge University Press.

34. Helen Nissenbaum. 2009. *Privacy in context: Technology, policy, and the integrity of social life*. Stanford University Press.

35. Nvivo 2017. Nvivo 11. (2017). http://www.qsrinternational.com/nvivo-product.

36. Changhoon Oh, Taeyoung Lee, Yoojung Kim, SoHyun Park, Bongwon Suh, and others. 2017. Us vs. Them: Understanding Artificial Intelligence Technophobia over the Google DeepMind Challenge Match. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. ACM, 2523–2534.

37. Lara O'Reilly. 2014. Here's One Way To Find Out Which Advertisers Are Tracking You Across The Internet. (2014). http://www.businessinsider.com/floodwatch-ad-tracking-chrome-extension-2014-10.

38. Javier Parra-Arnau, Jagdish Prasad Achara, and Claude Castelluccia. 2017. MyAdChoices: Bringing transparency and control to online advertising. *ACM Transactions on the Web (TWEB)* 11, 1 (2017), 7.

39. Frank Pasquale. 2015. *The black box society: The secret algorithms that control money and information*. Harvard University Press.

40. Pearl Pu and Li Chen. 2007. Trust-inspiring explanation interfaces for recommender systems. *Knowledge-Based Systems* 20, 6 (2007), 542–556.

41. Emilee J Rader. 2014. Awareness of Behavioral Tracking and Information Privacy Concern in Facebook and Google. In *SOUPS*. 51–67.

42. Ashwini Rao, Florian Schaub, and Norman Sadeh. 2015. What do they know about me? Contents and concerns of online behavioral profiles. *arXiv preprint arXiv:1506.01675* (2015).

43. Christian Sandvig, Kevin Hamilton, Karrie Karahalios, and Cedric Langbort. 2014. Auditing algorithms: Research methods for detecting discrimination on internet platforms. *Data and discrimination: converting critical concerns into productive inquiry* (2014).

44. Florian Schaub, Aditya Marella, Pranshu Kalvani, Blase Ur, Chao Pan, Emily Forney, and L Cranor. 2016. Watching them watching me: Browser extensions impact on user privacy awareness and concern. In *NDSS Workshop on Usable Security*.

45. Doc Searls. 2012. *The intention economy: when customers take charge*. Harvard Business Press.

46. Nick Seaver. 2013. Knowing algorithms. *Media in Transition* 8 (2013), 1–12.

47. Rashmi Sinha and Kirsten Swearingen. 2002. The role of transparency in recommender systems. In *CHI'02 extended abstracts on Human factors in computing systems*. ACM, 830–831.

48. Aaron Springer, Victoria Hollis, and Whittaker Steve. 2017. Dice in the Black Box: User Experiences with an Inscrutable Algorithm. In *The AAAI 2017 Spring Symposium on Designing the User Experience of Machine Learning Systems*. AAAI.

49. Darren M Stevenson. 2016. Data, Trust, and Transparency in Personalized Advertising. (2016).

50. Andrew Tate. 2017. The 15 Strangest Targeting Categories on Facebook. (2017). https://adespresso.com/blog/the-15-strangest-targeting-categories-on-facebook/.

51. Omer Tene and Jules Polenetsky. 2012. To track or do not track: advancing transparency and individual control in online behavioral advertising. *Minn. JL Sci. & Tech.* 13 (2012), 281.

52. Joseph Turow. 2017. *The Aisles Have Eyes: How Retailers Track Your Shopping, Strip Your Privacy, and Define Your Power*. Yale University Press.

53. Blase Ur, Pedro Giovanni Leon, Lorrie Faith Cranor, Richard Shay, and Yang Wang. 2012. Smart, useful, scary, creepy: perceptions of online behavioral advertising. In *proceedings of the eighth symposium on usable privacy and security*. ACM, 4.

54. Weiquan Wang and Izak Benbasat. 2007. Recommendation agents for electronic commerce: Effects of explanation facilities on trusting beliefs. *Journal of Management Information Systems* 23, 4 (2007), 217–246.

55. Jeffrey Warshaw, Tara Matthews, Steve Whittaker, Chris Kau, Mateo Bengualid, and Barton A Smith. 2015. Can an Algorithm Know the Real You?: Understanding People's Reactions to Hyper-personal Analytics Systems. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. ACM, 797–806.

56. WhiteHouse. 2016. Big Data: A Report on Algorithmic Systems, Opportunity, and Civil Rights. *Washington, DC: Executive Office of the President, White House* (2016).

57. Craig E Wills and Mihajlo Zeljkovic. 2011. A personalized approach to web privacy: awareness, attitudes and actions. *Information Management & Computer Security* 19, 1 (2011), 53–73.

58. Yaxing Yao, Davide Lo Re, and Yang Wang. 2017. Folk Models of Online Behavioral Advertising. In *CSCW*. 1957–1969.