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Computational Methods for Improving the Observability of Platform-Based Advertising

Daniel Angus^a , Lauren Hayden^b , Abdul Karim Obeid^a , Xue Ying Tan^a , Nicholas Carah^b , Jean Burgess^a , Christine Parker^c , Mark Andrejevic^d , Robbie Fordyce^d , Loup Cellard^c , and Julian Bagnara^c 

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ABSTRACT

The advertising ecosystem has been progressively reshaped by computational advertising models facilitated and controlled by digital media platforms. Meta and Alphabet, two of the dominant players in this ecosystem, have contributed significantly to industry disintermediation via the design and market dominance of their advertising systems, which in turn are symbiotic with their own business models, and feed on large amounts of consumer data generated by everyday platform use. The operations and impacts of these systems remain opaque and difficult to observe. Responding to this challenge, we present a methodological framework integrating cultural, legal, media, and computational perspectives to enable the observation of computational advertising. This methodology comprises three novel computational methods: direct data gathering from ad transparency libraries; automated data donation via participatory citizen science browser plug-ins; and a privacy-aware mobile screen capture app. We describe how our suite of computational approaches enables scalable and participant-situated research, overcoming limitations posed by restricted platform access to computational advertising data. Ethical considerations and practical implications are discussed alongside case study findings, further demonstrating the potential for these methods to inform regulatory debates and scholarly advancements in the field.

The development and deployment of computational advertising models by digital media platforms has transformed the advertising industry's business logics and practices (Huh and Malthouse 2020). Digital media platforms are interdependent with the new computational advertising ecosystem, both in terms of their technological contribution to advertising and the ways they mediate the institutional relationships among advertisers, agencies, buyers, data brokers,

media, and regulators (Helberger et al. 2020). While there is some diversity in the global platform and advertising ecology, a small number of multinational platform companies exercise outsized degrees of power; indeed, Meta and Alphabet constitute a duopoly in most markets (Kininmonth and Lobato 2023; van der Vlist 2022).

Meta and Alphabet provide advertising services across a range of platforms: Facebook, Instagram,

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Messenger, and the Audience Network (Meta); and Google Search, Gmail, YouTube and the Google Display Network (Alphabet). Unlike traditional media such as television and print, *digital media platforms* offer a suite of data-driven, self-service tools for advertising creative development, audience building and targeting, retail integration and campaign evaluation (Kininmonth and Lobato 2023). Through the provision of these tools directly to advertisers, Meta and Alphabet have created “walled gardens” (Kininmonth and Lobato 2023, 3081) that consolidated steps in the advertising process—from user data collection to ad creation, buying, and placement and to outcome measurement. The closed advertising systems created by Meta and Alphabet present limited opportunities for industry, regulators, researchers, and civil society to observe how they work and what effects they might have on the market, consumers, and public life.

In response, advertising professionals, journalists, and critical media scholars have documented concerns related to data validity, privacy, and industry disintermediation because of the Meta–Google duopoly. Some have developed experimental approaches to audit these advertising ecosystems to discern whether and how they produce racial and other forms of discrimination (Angwin, Tobin, and Varner 2017; Yurieff 2021; Sweeney 2013). Advocates across research and civil society have called for research that addresses the opacity of digital advertising ecosystems and the consequent limits on consumers’ ability to interrogate and interpret ads shown to them (Helberger et al. 2020; Edelson et al. 2019). In addition to individualized consumer transparency initiatives, advocates have also argued for forms of observability that enable monitoring of competition and consumer protection at larger market and social levels (Australian Competition and Consumer Commission 2020; Edelson et al. 2021).

In this article, we address the need for critical examination of the digital platform advertising environment through a combination of cultural, legal, media, and computational perspectives. We particularly focus on the methodological framework and associated computational tools we have developed to enable the observability (Rieder and Hofmann 2020) of advertising on digital platforms. Our approach involves a novel combination of participatory citizen science and computational research methods that engage with everyday media users to help donate observations of customized, ephemeral, and dynamic forms of digital advertising. In much of our work to date we have applied these methods to identify and

examine potentially problematic advertising activities (Gupta et al. 2023; Carah et al. 2024) or to interrogate specific issues such as explainability (Burgess et al. 2024); however, they are also intended to be broadly useful to researchers, regulators, civil society, and other actors interested in tracking advertising content and its delivery and reception within digital media ecosystems. Our suite of computational approaches has been developed over several years, often through data-sprints (Venturini, Munk, and Meunier 2016). Taken together they enable opportunities for rich and highly scalable participant-situated computational advertising research, enhanced through the use of novel and powerful computational techniques.

In what follows, we situate our work against the backdrop of current transparency initiatives undertaken by major social media platforms, initiatives that our methods both utilize and extend. We discuss how our methods are particularly suited to the current post-application programming interface (API) era, in which researchers have limited access to official platform-controlled APIs for observing platform content, networks and operations (Freelon 2018; Perriam, Birkbak, and Freeman 2020). We then present in sequence the three novel computational methods developed by our team to enhance advertising observability. These three approaches are:

1. Gathering data from ad transparency libraries provided by digital platforms
2. Participant data donation using a custom browser plug-in that automates the donation of Facebook ads encountered by citizen scientists when scrolling through their web browser feeds
3. Participant data donation using a mobile screen capture app that enables citizen scientists to donate ads they see across pre-defined mobile apps

The descriptions and discussions of each of these approaches are bookended with the findings from recent case studies that drew on the data and methods associated with them. These case studies include examinations of alcohol, “green”, and gambling advertising. Results from these case studies have already informed debates on advertising regulation in Australia (e.g., Consumer Policy Research Centre 2024; Meese 2024; Parker et al. 2024), and we suggest how our approaches might inform international regulatory debates and future scholarly work. Although we do not have the space here for comprehensive technical implementation detail, much of this information

is available in our technical and data report (Angus et al. 2024a) and other open-source repositories to which we refer throughout the article.

Ad Transparency and Observability on Digital Platforms

The broad public understanding, criticism, and regulation of advertising that developed with mass media in the 20th century depended on its publicness. Advertising could be apprehended as a public form of communication because *advertisements* were published in forms of media where researchers, civil society, regulators, archivists, ratings agencies, and industry bodies could see, collect, and analyze them. *Digital platforms*, by contrast, have created a form of “dark” advertising with characteristics that undermine the publicness required for observation and accountability (Yun and Strycharz 2023), challenging long-standing norms about advertising observability, accountability, and regulation (Saunders 2020). At the same time, the dominant economic model for the commercial internet has resulted in the dramatic proliferation of online ads and their displacement of other forms of more publicly accountable advertising (Crain 2021). By 2022, online advertising reportedly took up the majority of advertising dollars spent globally (Statista 2024). The fact that more ads are being served in a far less observable way raises important social concerns about accountability, given the cultural role played by advertising and the potential for discrimination, predatory, harmful, and false advertising.

As historians have noted, advertising is socially significant not simply as a means of selling goods, but also as a cultural form that shapes and reflects social values and aspirations. Media scholars have long argued that advertising played a central role in the rise of mass consumer society in the 20th century. As the historian T.J. Jackson Lears (1995) observes, advertising has collaborated with other social institutions to promote, “dominant aspirations, anxieties, even notions of personal identity” (1995, 2). In addition to its role in mobilizing consumption to keep pace with the productivity of industrialized mass production, advertising has a broader cultural significance. The media historian Michael Schudson (1984) argues that advertising, “may shape our sense of values even under conditions where it does not greatly corrupt our buying habits” (1984, 23).

Given its central cultural role in shaping attention and reinforcing social trends, much work has been done on the role played by advertising in reproducing

stereotypes, preconceptions, and dominant meanings and associations. Scholars and researchers have explored the role played by advertising in shaping attitudes toward female body image and beauty (Kilbourne 1990); racial preconceptions and prejudices (Wilson and Gutiérrez 1995); and class (Marchand 1985), among other areas of social life. As ads come to permeate contemporary life, the values and attitudes they select and reinforce become a core component of the general information environment and social atmosphere. The strategies and systems that shape this atmosphere bear close scrutiny.

With Saunders (2020), in referring to *dark advertising*, we mean that most ads on digital platforms are personalized, and hence not publicly available; ephemeral, quickly disappearing from the user’s view; and not independently archived (Carah and Brodmerkel 2021; Lury and Day 2019; Edelson et al. 2021). Furthermore, the ads themselves are *unstable* in the sense that each instance of an ad is dynamically assembled and augmented from an array of components (products, text, images, buttons). This instability means that while two consumers might each see an ad from the same advertiser, their ads might be highly customized, containing different color schemes, copy, buttons, and images—and even different products—that the ad model has predicted will appeal to them. With the rise of integrated generative artificial intelligence tools within platform ad models (Meta 2023), ads are likely to become even more unstable in these ways (Campbell et al. 2022). Another important characteristic of digital advertising is the automated model itself. To understand digital advertising, we must be able to observe, understand, and hold accountable the processes of automated decision-making that build audiences, target ads, and algorithmically tune ad content. In addition to the darkness of ads and the automated models that serve them to audiences, public observability is further complicated by the extraordinary volume of ads created and circulated.

Meta and Alphabet have responded to pressure from researchers, civil society, and regulators by creating “transparency” tools and features available on their own websites. These offerings tend to take two forms. The first is explanations to individual users about the ads they see and why they are seeing them, such as Meta’s WAIST (Why Am I Seeing This?) feature, which is embedded in the graphical interface of Meta’s apps. These features usually present basic claims about the link between a user’s interests or behavior and the placement of a particular ad, but do not provide explanations of patterns of ads a

consumer sees over time, how the individual consumer's ad experience compares with others or positions them as part of a group, or how data are shared between advertisers, data brokers, and platforms (Kim, Barasz, and John 2019).

Second, platforms have created transparency libraries where the ads placed by advertisers on the platform can be viewed. However, the accessibility, searchability and durability of these archives vary. These libraries were largely a response to regulatory requirements for the disclosure of political advertising, especially in the United States and European Union (EU), starting with Facebook, Twitter, and Google in 2018 (Leerssen et al. 2019). In the EU, the Digital Services Act (European Union 2022, Article 39) now requires designated "very large online platforms" such as Meta and Alphabet to "compile and make publicly available" a repository of all ads. These repositories must be available through APIs for 1 year from when the advertisement first appeared and include information about "whether the advertisement was intended to be presented specifically to one or more particular groups of recipients and if so, the main parameters used for that purpose" and "the total number of recipients of the services reached" (European Union 2022, Article 30). Under the Digital Services Act (Article 40), "vetted researchers" may also be provided access to data "for the sole purpose of conducting research that contributes to the detection, identification and understanding of systemic risks... and to the assessment of the adequacy, efficiency and impacts" of risk mitigation measures. These provisions have been criticized, however, for maintaining secrecy of data regarding the operation of the design and functioning of the algorithmic recommender systems at the heart of the advertising models and privileging self-regulation regarding the degree of information provided and access to researchers (Marconi 2022). To date, Meta and Alphabet are the only platforms to offer ad transparency libraries outside of the EU, albeit with extremely limited information for advertising that falls outside of the category of political (or "issues-based") advertising (Carah et al. 2024).

The three approaches we develop in this article extend beyond the affordances and limitations of advertising transparency libraries provided by major digital platforms (Carah et al. 2024). In our own audit of the ad transparency libraries, we found a number of limitations including the following: (a) the archive of ads is not permanent or easily searchable; (b) the ads cannot be easily extracted for independent analysis; and (c) either no information or very limited

information is provided on targeting, volume, spend, or reach. While we focus here mostly on Meta and Alphabet, we note that other platforms use different advertising systems. WeChat for instance, requires a minimum number of users in a country before it commences with localization of programmatic advertising.

At the time of writing, outside of the EU, the Meta Ad Library only publishes and indexes general (non-political) ads while these ads are currently running (i.e., "active") on any of Meta's four platforms (Facebook, Instagram, Messenger, and Audience Network), whereas political or social issue campaign advertising is stated to be available for 7 years after publication. Metadata on audience targeting, ad spend, and reach are similarly limited to political and social issue ads. While political and social issue advertising can be accessed and downloaded through an official API (prior approval from the platform is required for access), general advertising is only visible through a web-based dashboard. Users can search for ads by keyword or Page Name and have access to some limited data filtering and sorting options. The dashboard is limited to displaying ads one-by-one in a grid layout pattern and does not provide aggregated statistical outputs or other high-level comparison features. The one exception is the "ad spend tracker" for political and social issue ads that provides a line chart of total ad spend per page, over a set range of time, as chosen by a user.

The Google Ads Transparency Center indexes ads on YouTube, Gmail, Search and Display networks, although only from verified advertisers (Google Ads Transparency Center n.d.). Ads are retained for up to 365 days, although, similar to Meta, political advertising is available for 7 years. Also similar to the Meta Ad Library, targeting, spend, and reach metadata on nonpolitical advertising are significantly limited or non-existent. Ad data are accessible through a public dashboard, although search is limited by precise matches to advertiser or website name rather than text that may appear in the ad copy, and no filtering or sorting options are available.

For both Meta and Alphabet, the data and affordances of their ad archives produce a thin form of transparency that limits scrutiny of the advertising system and prevents thorough analysis of ads at scale. Some refer to these transparency initiatives as "archives"; however, it is clear that they lack many of the properties generally understood to be fundamental to an *archive*, including data permanence, completeness, and discoverability. A more fitting analogy

would be that of a *library*, albeit one for which access is tightly monitored; patron movement significantly inhibited; and most of the books are glued shut, copies cannot be easily made, and documents are shredded after a short time.

There are three significant problems with the limited scope of the content of these platform-provided archives. First, as Hartmann (2021) notes, the conventional limitation of scope to “political” or “issue” ads ignores the reality that exploitative misinformation is not necessarily declared upfront as “political” and that political ads can “slip through the cracks” more generally. Second, the arbitrary distinction at work here ignores the important role that all forms of advertising play in shaping our cultural norms and values and hence their significance for society. Third, as Borenstein and Taylor (2023) show, demographic, behavioral, and geographically targeted advertising in general poses a range of risks to consumer welfare. These risks are not limited to one product or industry, but rather a consequence of opaque computational ad models. For example, Borenstein and Taylor (2023) highlight how behavioral targeting, such as ads targeted based on web browsing history, can result in inappropriate profiling and exploitation of consumers susceptible to harm from addictive commodities like online gambling. To maintain public oversight, we need independent observability, not only over all categories of advertisements, but also over the ad systems that target, customize and deliver them.

The EU Digital Services Act has required Meta and Alphabet, as well as other “gatekeeper online platforms,” to improve transparency by publishing geographic and demographic information about the targeted and reached audience for all ads displayed in the EU (Woollacott 2023). However, none of these measures address the issue of independent verification of information provided by the platforms. Particularly

with respect to metadata such as audience and reach, the measures provided by the platforms via any of their variously limited transparency dashboards lack external validity (Maroni 2023). There is a need for *observability*—not just *transparency*—to enable greater platform accountability (Rieder and Hofmann 2020).

Novel Methods for Making Digital Advertising Observable

The existing and emerging methodologies for collecting online ads and contextual data about them are diverse, as researchers adapt to changing interfaces, policies, and attitudes from platforms and their users. These changes have led to methods that range from highly platform-specific data access solutions comfortably in the realm of computational methods through to investigatory methods, such as app walkthroughs (Light, Burgess, and Duguay 2018), or scroll back interviews (Robards and Lincoln 2019), that can be redeployed across multiple contexts but are intensive and time-consuming. In some cases, approaches and tools become unviable while platform features and access change, along with changing ethical frameworks and norms about data collection.

We characterize methods for observing digital advertising along a spectrum of “thin” to “thick” approaches, in which *thin methods* are those that may seek to gather advertising where an audience is implied, but not directly sampled or included in any collection and analysis activities (see Figure 1). As an example, methods used to collect data from the platform provided advertising transparency dashboards are thin methods because they either wholly exclude or collate details relating to users under broad demographic categories, and they do not provide any information relating to specific user experiences of when and how they receive ads. At the other end of the

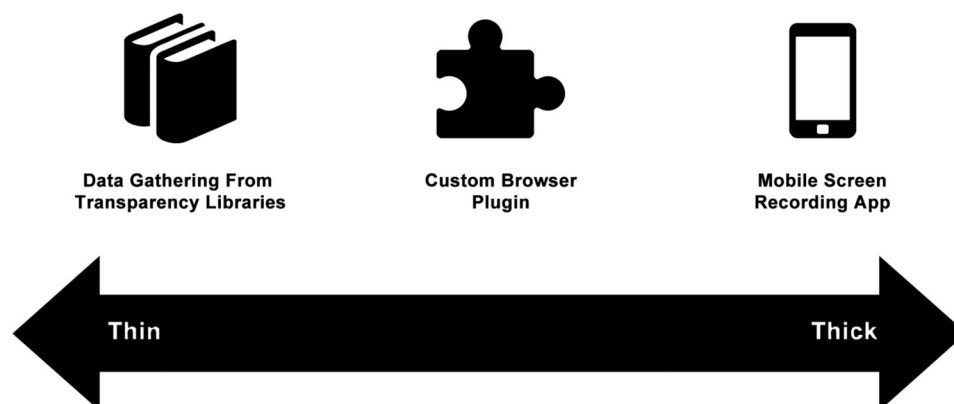


Figure 1. Our three complementary methods situate along a spectrum of thin/thick user-focused methodologies.

spectrum, *thick methodologies*, like participatory and qualitative audience or user research, directly include or involve end users through close observation of not only the forms of advertising they receive but how ads are woven into their everyday media experiences, perhaps even ascertaining specific reactions, perceptions, or feelings they may have in relation to these ads. Approaches that involve participants “donating” ads to researchers lie somewhere in the middle of this spectrum. The act of using a computational tool to donate ads that help researchers build a collection for analysis requires research participants to consent and support the aims of making digital advertising more observable, but the method only becomes genuinely “thick” if the citizen scientists are then involved in helping researchers interpret and make sense of the ads they are seeing (Munk, Olesen, and Jacomy 2022).

We offer our descriptions of these methods as resources for implementation and adaptation by researchers within their own contexts using their own infrastructure. In addition, while we make reference to data collected using these methods for the purposes of showcasing their affordances and limitations, at present we do not publicly share any of the data collected in our own use of these methods.

Our methods suite responds to the growing disjuncture between web- and mobile-based platform offerings. Whereas “once upon a time” we may have been able to assume close parallels between the web and mobile versions of these various platforms, today Instagram, TikTok, WhatsApp, and many other services now offer more functionality, and a significantly different user experience on a phone app than on a computer. This lack of parallelism has implications for the design of computational advertising methods in that both major mobile operating systems, iOS and Android, use a security principle of “sandboxing,” which makes it extremely difficult to directly access data from an app. As a result, programmatic data access to mobile apps is often highly restricted.

Historically, mobile sandboxing has not been a significant issue for computational advertising research because many platforms have been open to researchers accessing some data through computational methods that access a platform’s database directly over the internet. However, as discussed, the dashboards and official platform APIs are significantly limited.

In the following sections we will show how, when taken together, these methods provide a highly complementary, scalable, and robust suite of methods to study computational advertising, particularly in a post-API era.

Whitelist Download

Platform-provided ad transparency dashboards and APIs are limited with respect to data permanence, completeness, and discoverability. Here, observability and completeness are in tension. Whereas observability is limited by the data that platforms choose to provide, a glut of information may be created if platforms provided all ads and variations of ads published, and archived them permanently, which would end up perversely obscuring observability. Setting aside completeness of ad collections, it is however possible to address issues of permanence and discoverability through the creation of independent advertising databases that use transparency libraries as a primary data source. Such databases can be used to maintain copies of ads even after these are removed by the platforms, and it is possible to add additional data indexing and enrichment to assist in the identification of features of interest in collected ads beyond the search functionality provided through the platform dashboards.

The *whitelist download* approach utilizes web scraping to obtain copies of advertising material sourced from the transparency dashboards, for which the technical implementation details can be found at Tan and Angus (2024). Advertisers of interest are compiled into a “master-list,” and the dashboard services offered by the major platforms are consistently probed by an automated script to identify and subsequently make copies of ads of interest. Copies of ads, including the ad creative and any associated metadata, are stored in a secure database on the researchers’ infrastructure of choice, and these ad collections can then be used for various analytical purposes, including being made available through a research dashboard (see Figure 2).

The whitelist download method is particularly appropriate for research involving nonpolitical advertising, given that outside the EU the major platforms do not provide searchable archives of nonpolitical advertising that include inactive (historical) ads. Even for political advertising content, however, the dashboards and APIs provided by the platforms cannot necessarily be considered robust research infrastructure given that they are governed and maintained by commercial platforms. For this reason, some groups have already developed their own third-party tools that provide researchers with more accessible statistics and searchability of these dashboards. Examples of third-party advertising analysis dashboards include the PoliDashboard (Mai et al. 2024), and the Illuminating project (Stromer-Galley et al. 2021). These tools, and

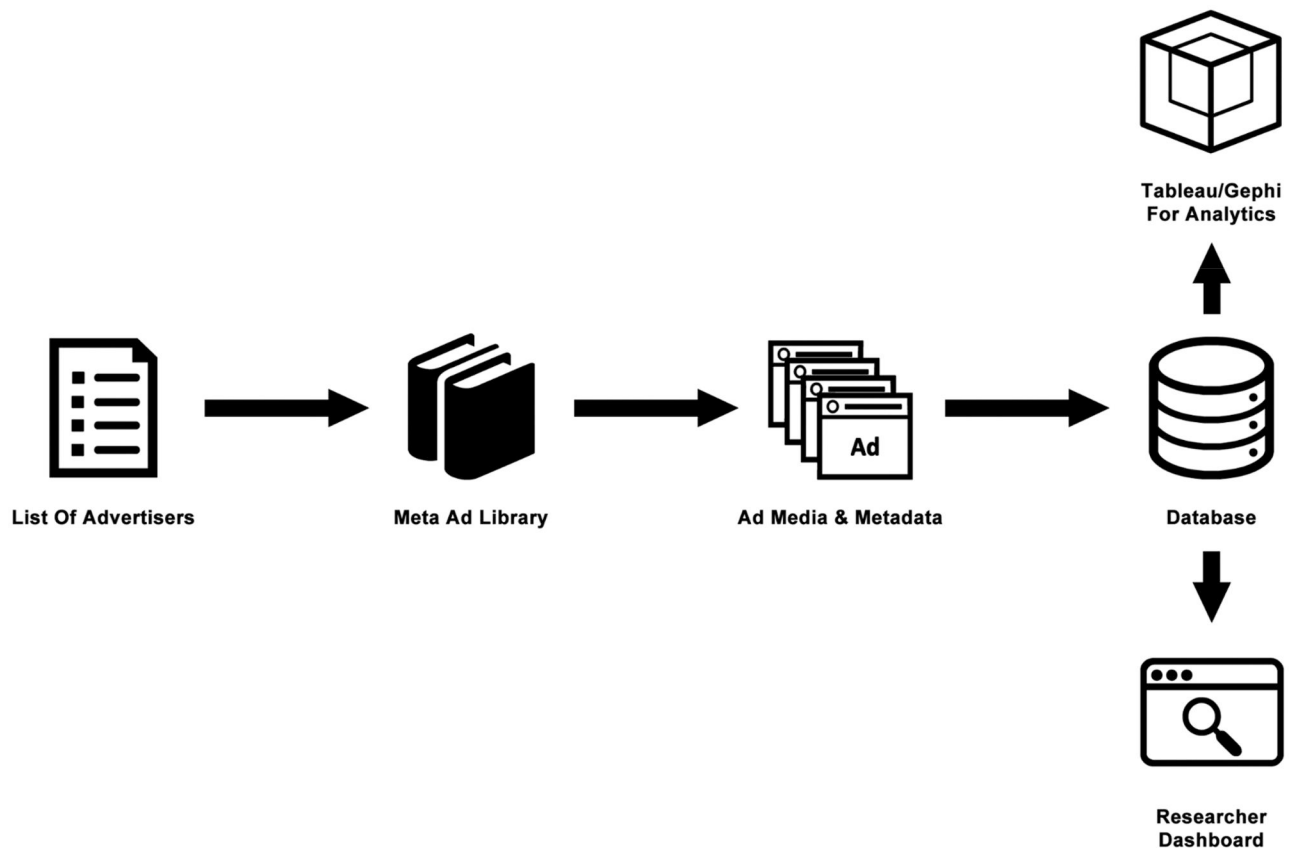


Figure 2. The whitelist download method involves the creation of a “master-list” of advertisers; ads from these sources are then repeatedly gathered from the platform ad libraries and added to a database that feeds various analytical outputs.

others, have focused on political advertising, and largely follow a similar “whitelist” methodology, whereby researchers or other interested parties establish a “master-list” of political accounts/pages to track, locate, and connect the entities of interest to a known platform ID, then performing regularized data acquisition or simply providing an interface that interoperates in a live or semi-live sense with the political ad APIs provided by the platforms. Some connect additional politically relevant metadata such as party affiliation or electorate information (e.g., house/senate/leadership) to enable additional forms of direct correlational analysis between ads and relevant political insights.

As a practical example of this method in action, we have been tracking Australian alcohol producers, retailers, and venues as part of a multi-year study into alcohol marketing in Australia. The work seeks to examine the prevalence and messaging of this alcohol advertising on Meta’s platforms over a 3-year period. For this work, a list of 1123 advertisers of interest were first curated, informed from a recent audit of major alcohol producers and distributors (Beck, Pierce, and Stafford 2021). Using the list of brands, retailers, and venues, the advertiser names were translated into Meta page IDs because each advertiser has

a unique ID in the Meta Ad Library. A page ID allows us to collect ads only from that advertiser to exclude false positives for some advertisers that have similar names. Additionally, some larger brands have different associated accounts/pages for advertising in different countries/regions, and the page ID allows us to restrict our analysis to the right account(s).

While the capture of advertising content is highly automated, the whitelist curation and ID linking is a highly manual process, requiring researchers to manually identify and verify the accuracy of all platform-specific ID and advertiser pairings. A simple programming script is then run weekly, alternating among Thursday, Friday, and Saturday, collecting from the same list of page IDs each week after account reauthentication and renewal of cookies. The rationale being that there may be more alcohol advertisements on weekends from a marketing perspective. This weekly collection allows us to capture short-lived ads before they are made inactive and removed from the platform’s library but is not as intensive as a daily collection routine, which could trigger automation prevention measures from the platform.

While most page IDs do not change, some accounts/pages have different IDs after a certain period for an unknown reason. This situation may

not be discovered immediately as the same list of page IDs is used each week for ad collection; however, it is possible to examine the number of ads returned for each source and flag those that are no longer returning ads at an expected volume for further investigation.

Case Study 1: Alcohol

As part of our research into alcohol advertising we used the whitelist download method to inform a 1-year snapshot study that details the volume of alcohol advertising (delineated by retailer/producer/venue); the nature of specific ad construction, such as the ways that Call to Action (CTA) buttons are used to direct sales of alcohol; and seasonal ebbs and flows, as well as how these elements impact the messaging and creative characteristics of these ads (Hayden et al. 2023). Using this method, we were able to collect and analyze 39,820 alcohol ads over a 1-year period. We analyzed this collection of ads to track changes in advertiser practices in terms of the volume and content of ads published on Meta services over the course of a year. In the case of alcohol advertising, we were able to illustrate that alcohol retailers produced many more ads than alcohol producers, and that retailers increasingly integrated “buy” buttons in their ad formats. These data enabled us to track the integration of advertising and retail into digital platforms.

Although we can collect the ads published on the platform, what remains unknown is how often people are exposed to these ads and how they are being targeted. Not being able to observe how alcohol ads are targeted is a problem because of concern about how ads for harmful and that addictive products like alcohol may be targeted to people with high alcohol use or those who are recovering from alcohol addiction or dependency (Borenstein and Taylor 2023). The whitelisting approach both builds on the ad library to create a permanent and searchable archive of ads, while also highlighting serious shortcomings in the data provided by platforms. In short, transparency libraries provide a dashboard of some of the ads, but thwart the capacity to observe the computational characteristics of digital advertising.

Data Donation via Browser Plugins

Although the whitelist download approach is useful in collating archives of advertising creative, it provides few insights into the specifics of the targeting and temporal sequencing of these advertisements. For the

case study of alcohol advertising just described, we know from related research that these alcohol advertisements might appear with greater frequency in closer proximity to the weekend, but also in response to specific purchasing or lifestyle activities of users (Robards et al. 2022). Even with transparency dashboards providing limited targeting information, as is the case with political advertising, this information is abstracted away from users such that we cannot know when these advertisements appeared in their news feeds, what other ads were seen by them, and other more personal user information. To respond to these limitations, we pioneered another technique: a *data donation browser plugin*, focused on collecting Facebook advertising content and user targeting information for extensive offline analysis (see: Angus et al. 2024a, 2024b; Burgess et al. 2022). Data donation methods, particularly those used in relation to digital platforms, are a rapidly developing area of development and interest (Araujo et al. 2022), particularly given the limitations and increasing instability with official platform APIs (Bruns 2019). Ohme et al. (2023) demarcate data donation into a variety of categories, and according to their definition this plugin could be considered by their definition as a form of user “tracking.” *Tracking* is defined as a user-centric data collection method that gathers data in real-time as it is delivered/consumed by enlisted users.

This plugin is at the heart of the multi-year Australian Ad Observatory study, which throughout 2021–2023 successfully enlisted more than 2000 volunteer Australian Facebook users, who contributed more than 700,000 ad observations to a secure research database via the plugin (see Figure 3). Volunteers enrolled in the project by downloading and installing the dedicated browser plugin and completing a brief demographic questionnaire. They were sourced from all around Australia, mostly thanks to a partnership between our research team and the national public broadcaster, the Australian Broadcast Corporation, which ran a series of stories (online, radio, and television) on the research aims and expected outcomes of the project. Once installed and registered by any given participant, whenever they then engage with the Facebook platform on their laptop or desktop computer, the plugin captures sponsored content—and only sponsored content—from their Facebook News feeds, sending this advertising data to a secure database, in the process connecting the ad to their pre-registered, de-identified, demographic details.

The effort builds upon work from ProPublica and New York University (NYU), which together developed

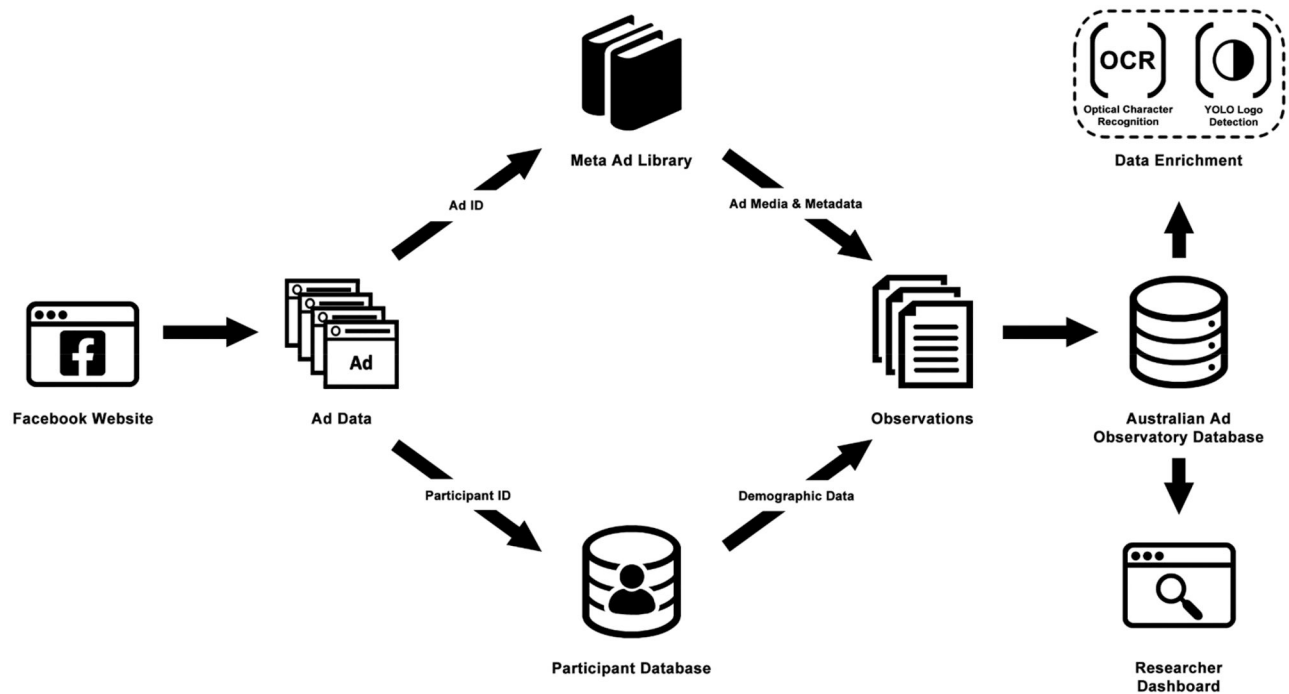


Figure 3. The Australian Ad Observatory.

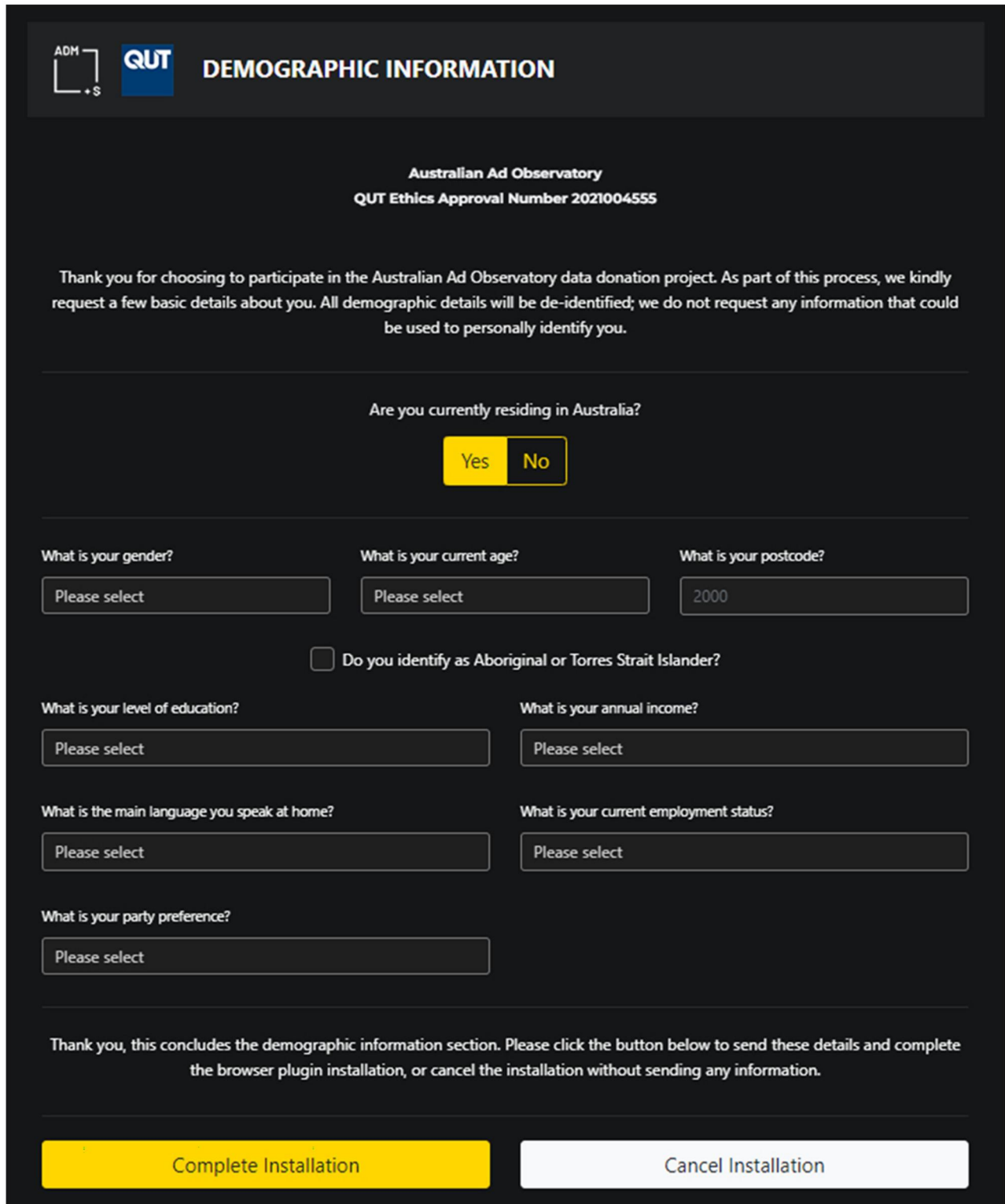
a browser plugin to examine Facebook’s algorithmic advertising model (ProPublica 2020) as well as pilot research from our own team (Andrejevic et al. 2022; Trott et al. 2021). These efforts themselves extend and situate among similar efforts made by investigative journalists and researchers undertaking hypothetical or experimental explorations of online advertising systems (Andreou et al. 2019; Angwin, Tobin, and Varner 2017; Beraldo et al. 2021; Datta, Tschantz, and Datta 2015). Our original contribution combined this pilot work through a complete code re-implementation of the plugin (Obeid 2023a), in addition to significant extensions and improvements in the downstream data storage (Obeid 2023b) and analysis pipelines (Obeid 2023c), discussed in following text.

The plugin has been developed to ensure compatibility with current plugin standards for the desktop versions of leading web browsers: Google Chrome, Mozilla Firefox, and Microsoft Edge.¹ The choice of web browsers was informed from Australian market share data on browser usage and these stores approving the plugin for download by users. Chrome (~64%), Edge (~13%) and Firefox (~5%) are three of the four leading web browsers in Australia by total desktop browser market share. Safari (~15%) ranks second; however, its isolated software development conventions separate it from the “Chromium”-based software that unites browser extensions across all other browsers. Technical limitations of the extension

development environment of Safari, specifically the absence of necessary header modification capabilities in the official Safari extension API (Apple Developer 2024), made it highly impractical for us to pursue development of the plugin; for these reasons, Safari was excluded from our sample.

Upon plugin registration, participants are redirected to a university-hosted website to provide informed consent (see Figure 4) and to complete a concise demographic questionnaire, providing optional information such as age range, gender, postcode, education level, annual income range, main language spoken, employment status, political preference, and Indigenous identity. These responses, while valuable for investigating demographic variations in advertisements, ensure user anonymity, because the plugin does not require or access personal information such as names, email addresses, or other such data. Upon completing the questionnaire each user receives a unique private key, linking their Facebook advertising experience to a dedicated marker and allowing them to view their personal ad archive. This private key is meaningless to any malicious third party in the unlikely case of a data breach.

After registration, whenever users are browsing Facebook and encounter advertising content, this content is identified by the plugin, extracted from the webpage Document Object Model (DOM), and sent to our secure database along with their unique private key. In addition, users can at any time open the plugin to retrieve a listing of all ads they have encountered since



ADM **QUT** **DEMOGRAPHIC INFORMATION**

Australian Ad Observatory
QUT Ethics Approval Number 2021004555

Thank you for choosing to participate in the Australian Ad Observatory data donation project. As part of this process, we kindly request a few basic details about you. All demographic details will be de-identified; we do not request any information that could be used to personally identify you.

Are you currently residing in Australia?

Yes **No**

What is your gender? What is your current age? What is your postcode?

Do you identify as Aboriginal or Torres Strait Islander?

What is your level of education? What is your annual income?

What is the main language you speak at home? What is your current employment status?

What is your party preference?

Thank you, this concludes the demographic information section. Please click the button below to send these details and complete the browser plugin installation, or cancel the installation without sending any information.

Complete Installation Cancel Installation

Figure 4. User consent form used by volunteer participants when registering the browser plugin.

installation of the plugin in their own private ad library. This aspect of the method builds some reciprocity into the project by providing users with a useful digest that they can use to reflect on the nature of their Facebook personalized ad experience.

For data enrichment purposes, when ads are sent to the secure database, they trigger a query to Meta's Ad Transparency Library via the same process used in the whitelist download method discussed earlier. Social issue, election, or politics-related ads benefit

from Meta's (2024) Ad Library API, whereas nonpolitical ads use a mechanized web-browsing session to access Meta's Facebook Ad Library website. This approach allows us to associate additional metadata to each ad, which may include information on reach, ad spend, and higher-resolution ad images.

Image data for each ad, including still frames, are also sent through an image analysis pipeline. Techniques including optical character recognition, brand logo detection, object detection, and image saliency have proven valuable, particularly in the automatic detection of political logos during the 2022 Australian federal election. In that case, we were able to use logo detection to identify Facebook ads that were suspected of failing to conform to political advertising standards required under the Commonwealth Electoral Act 1918 (Karagic, Worthington, and Workman 2022).

A custom research dashboard is provided to approved researchers (see Figure 5), which allows researchers to search the entire ad database using Boolean queries that can incorporate free text, demographic information, or any other ad metadata, in addition to image searches (for brand logos, as described above). Returned searches can be qualitatively explored within the dashboard, or exported (with images/videos, and metadata in .csv or .json formats) for additional downstream analysis.

The database and dashboard processes are facilitated by technologies offered in Amazon Web Services; namely, they involve AWS API Gateway and Lambda for data acquisition and transformation. These

technologies were selected for their implementation of serverless architectures and ability to manage unpredictable data donation timing and rates of donation. We cannot predict when data donations will be captured by participants; hence, our infrastructure needs to have high "up-time," and this requirement will be a key technical consideration for anyone seeking to replicate or build on our approach. More details on this technical implementation, as well as detailed case studies, can be found in Angus et al. (2024b).

Case Study 2: Green Ads in the Australian Ad Observatory

With many consumers wanting to make environmentally conscious purchases, advertisers often respond by *spruiking* (proclaiming) their environmental "green" credentials (Banerjee, Gulas, and Iyer 1995; Kwon et al. 2024). However, regulators and consumer advocacy groups worldwide have highlighted the increasing tendency of online advertisers to make "concerning" environmental claims, which range from vague, meaningless, or difficult to substantiate, to outright false and misleading (ACCC 2023; Burry 2022; Competition and Markets Authority 2021).

These trends can lead to multiple harms for consumers, businesses, and the environment. Consumers may spend more on products they believe to be green, and risk wasting money due to untrue claims; and in contexts where *greenwashing* is prevalent, it can erode

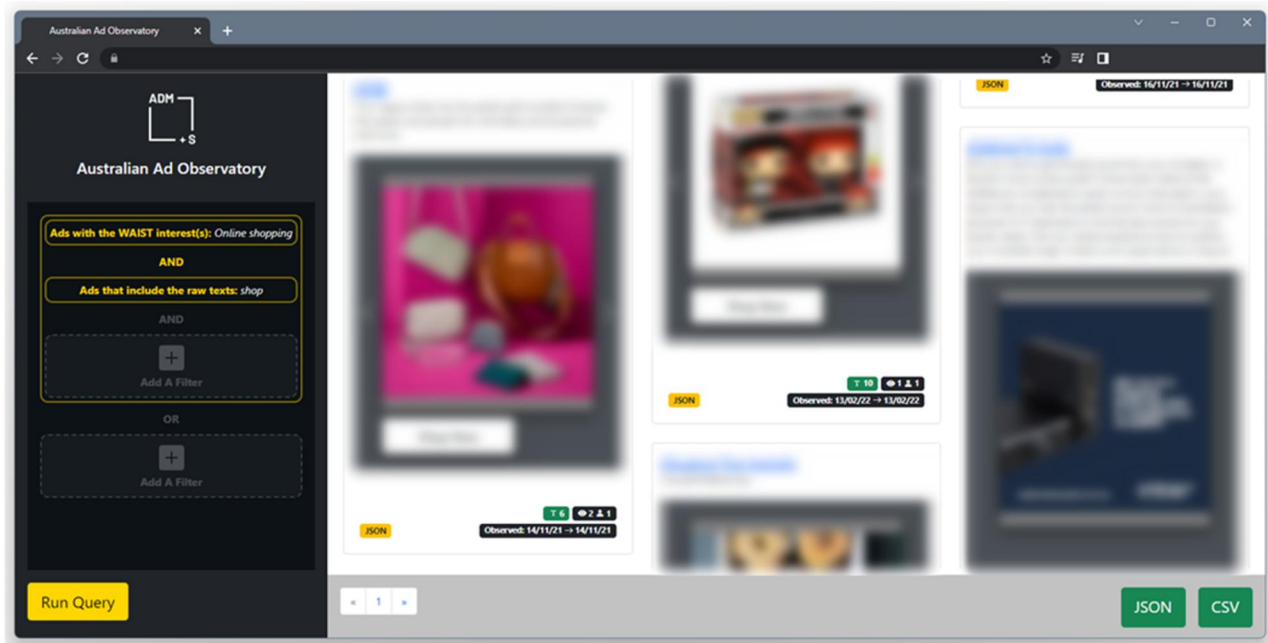






Figure 5. The research dashboard provides an easy-to-use GUI for researchers who can perform Boolean searches to filter specific collections of ads from the ad donation database, enabling further analysis and inquiry.

consumer trust in labels, certification schemes and those making genuine green claims (Gupta et al. 2023). Misleading green claims can also impact market competition. Companies that engage in green-washing may gain an unfair competitive advantage over businesses that use green claims responsibly because more sustainable practices can often result in higher costs and prices. In addition, those engaging in misleading green advertising can take advantage of consumer desires to “do good” through ethical and sustainable consumerism, manipulating consumers in a way that negatively impacts their ability to make sustainable choices, reduce environmental harms, and combat climate change more generally. A recent survey found that 45% of Australian consumers assume that a trusted third party is fact-checking green claims, highlighting the need for tools that improve the observability of platform based-advertising (Burry 2022).

Australian Ad Observatory researchers combined the technologies utilized in the whitelist download and browser plug-in methods to create a comprehensive 12-month snapshot of green advertising on Facebook in Australia. Through the Ad Observatory’s researcher dashboard, researchers were able to search the wider database for advertisements containing specific terms often associated with green claims. This list of search terms was based on environmental terms identified by consumer regulators as likely to be problematic, including “environmentally friendly,” “sustainable,” “compostable,” “biodegradable,” and “green” (Rickard 2022; ACCC 2023), and responses to a recent survey identifying which words and messages consumers associate with green and environmental claims (Burry 2022). The search was conducted iteratively using 27 search terms in total, and Boolean operators to reduce noise. The resulting dataset was then manually cleaned to ensure that each advertisement contained green claims, leading to a database of 8,498 unique advertisements from 488 advertisers observed 30,008 times over the 12-month period. We found that close to 6% of all advertisement observations contained a green claim of some kind.

The green claims dataset generated from this process has been used for two outputs addressing different research questions; a snapshot report coauthored with the Consumer Policy Research Center (CPRC) (Gupta et al. 2023), and an in-progress article examining how Facebook’s ad model tunes users toward patterns of environmental narratives, esthetics and themes, which are each discussed further in following text.

The CPRC snapshot report (Gupta et al. 2023), outlines the prevalence and nature of green claims made on Facebook. The reports output addresses policy-oriented research questions concerning the volume and characteristics of potentially unlawful online advertising. The report found that environmental claims were most commonly made in the energy, household products, and fashion sectors; the most frequently observed terms were “clean,” “green,” “sustainable,” “bio,” and “recycled/recyclable”; while many green emojis, including the green tick  leaves, , earth symbols  and the Mobius loop recycling symbol  featured prominently. The report found that such environmental terminology had no common meaning, with similar terms used in various and inconsistent ways. While some ads provided details to support their environmental claims, often it was difficult to ascertain the accuracy of any claims being made. It was also found that color and esthetics played an important role in environmental advertising, with frequently identified use of green, blue, and beige hues implying an environmental benefit that may not exist (Gupta et al. 2023). With the Australian Competition and Consumer Commission (ACCC) taking an increased interest in problematic green claims, the results of our methods have contributed to policy debates around green advertising (Briggs 2023; Consumer Policy Research Centre 2024) and informed the ACCC’s review of its guidance for business on environmental and sustainability claims. This contribution highlights the importance of observability tools in assisting regulators to take enforcement action against misleading advertisers.

The second stream of analysis from the green ads case study uses the tools developed by the Ad Observatory to allow researchers to better understand the relationship between consumers and the flows and assemblages of ads that they see (Lyons et al. 2023). As computational advertising models delegate audience segmentation to machine learning algorithms, we are witnessing a shift away from large-scale demographic targeting (Beauvisage et al. 2023) toward the continuous optimization of algorithmic flows (Lupinacci 2024) that aim to tune and customize sequences of ads in ways that stimulate affective responses amongst consumers (Brown et al. 2024). The functionality provided by the Ad Observatory’s plug-in allows researchers to view users’ donated ads in sequential order, allowing researchers to identify flows, narratives and esthetics of advertisements and how they relate to the temporal sequences in which they are fed to individual users. We use the Ad

Observatory together with a combination of statistical techniques and qualitative coding to identify clusters of individuals who receive a large proportion of green ads in patterns of frequency, time, and adjacency to other ads.

One of our research aims is to understand how consumers are being tuned toward patterns of environmental consumption via a combination of textual elements and associated imagery, esthetics, and subjective affect (Parguel, Benoit-Moreau, and Antonia Russell 2015). To achieve this aim, using our original green claims database we identified 20 Ad Observatory participants with the highest proportion of green advertisements, and downloaded their entire dashboards to examine their ads in sequential order. Homing in on individual browsing sessions that prevalently featured ads in our green claim database, we have been able to identify various archetypes or “vibes” of green consumerism that emerge as products of algorithmic associations and approximations (Brown et al. 2024; Phan and Wark 2021). By examining these sessions in combination with each user’s most frequent advertisers, we can see how algorithmic patterns of association create emergent esthetic assemblages of environmental consumerism (Miller and Rose 1997) that flow through users’ feeds. While our Seeing Green report informs and assists policy makers and regulators, our work on green vibes in the flow of ads investigates how algorithmically selected sequences of ads may appeal to observers’ emotions of concern or fear relating to ecological crises, their sense of guilt and duty to consume in an ethical and environmentally responsible way, and their desire to connect with nature. We expect to be able to extend this approach in future work to enable social media participants to observe their own ad flows and how their own activity online may be combining with ad tech to co-create green consumer subjectivities.

Mobile Ad Toolkit

The browser plugin, while not necessarily achieving the same scale (per advertiser segment) as the whitelist download, is useful in connecting advertising content to data on user demographics and the sequencing of ads in user feeds. A fundamental limitation of the browser plugin, however, is that most users engage with these platforms via mobile devices, hence a complimentary mobile-first approach is required to facilitate the capture of ads that are delivered via a mobile device.

Screen capture methods, whereby researchers or research participants use a phone’s onboard systems to directly capture screenshots or engage in video recording of platforms, are commonplace in many disciplines beyond just computational advertising research. An additional benefit with mobile screen capture is that they tend to not be subject to interference from platforms and, indeed, can be conducted without the platform’s knowledge. Screen capture methods are also relatively unambiguous about the arrangement and nature of content, and do not have to contend with content removal because they capture a snapshot of the platform at a specific point in time for a specific user. This approach can be valuable for many kinds of projects, especially those that are ethnographic in nature.

The most significant limitations and considerations for screen capture methods are the management of highly sensitive participant data, especially for large-scale projects, and the flattening of multimodal web data into static low-resolution images. Although screenshots capture an interface effectively, they are not ideal for creating searchable data repositories. The process of coding and analysis can be particularly time consuming, and sorting contributions from multiple researchers and research participants means that for most approaches there are practical limits on a project’s scale. We tackle both limitations in our mobile capture approach.

The Mobile Ad Toolkit extends upon the work of Krieter (2019), allowing individuals to donate advertisement data they have been served on the Facebook mobile app, for which the technical implementation details can be found at Obeid (2024). Participation involves the installation of an Android-based mobile app, which can be downloaded from Google’s official Play Store. Like the browser method, at the start of installation, demographic details (including characteristics such as age, gender, and postcode) are requested from individuals. As with the browser method, no personal information that could be used to directly identify individuals is requested, and only data corresponding to general demographic characteristics are collected. Providing these details concludes the “in-app” registration process, and individuals can then access the app’s intended functionality. As hinted above, this approach is limited to Android devices because iOS implements several controls that significantly limit the use of screen recording.

App functionality involves screen-recording the individual’s mobile device screen. The user activates the screen-recording feature and is prompted to

provide permission to the application so that it can record the mobile device’s screen as a background process while the user engages with their typical device usage. Screen recording involves the app taking still images at a low frame rate and low resolution and storing these locally on the user’s mobile device. No data are transmitted off the mobile device by the app during this process, and this screen capture process is triggered whenever the device is in an active “awake” state.

When the device is placed onto a charger, the app triggers an evaluation of image frames stored by the screen-recorder. The evaluation first involves an image analysis technique, specialized to identify imagery distinctly associated with the Facebook app. When relevant imagery is identified, a logo detection technique secondly assesses the presence of the “Sponsored” sub-heading that demarcates Facebook advertisements. If the two conditions are met, the given frame is cropped to the advertisement content. Aside from the cropped advertisement image, no other images from the mobile device are retained, and the remaining cache of images are deleted from the user’s mobile device. This image-based ad detection approach is presently being extended to encompass ads from other major platforms, using distinguishing visual features that reliably denote ads.

The cropped advertisement image is then sent to a secure API endpoint, along with a unique credential that identifies the individual who submitted the data, like the browser method. Once collected, the frames are evaluated by a distribution of Jaided AI’s (2023) “Easy OCR” image analysis software. Text details identifying the relevant advertiser are extracted to query the Facebook Ad Library API and Web Interface. These services may return official versions of the advertisement that can be used to enrich those obtained from screen-recordings. The two alternatives are aggregated to create a composite version of the

advertisement that is furthermore associated with details of the observation(s), such as the time of observation and device model, as well as the earlier mentioned demographic characteristics corresponding to the individual(s) who were served the advertisement. All these data are stored within a relational database, to which the user may refer directly within the app to review their personal archive of advertisements they recorded (see Figure 6). From this point all data can be indexed and reviewed using the research dashboard originally developed for the browser plugin method. This approach includes similar data indexing, enrichment and Boolean query support, the only difference here being that data have been sourced from a mobile device.

Case Study 3: Gambling Ads in the Australian Ad Observatory

Gambling in Australia is a significant issue, including sports betting, electronic gaming machines, and online casinos. Australia has the highest per capita gambling losses in the world: in 2022 Australians spent approximately AUD\$25 billion on legal gambling from an adult population of 20.5 million (AIHW 2023; ABS 2023). Australia has a significant issue with problem gambling, which disproportionately effects young men; 70.7% of men age 18–34 years are at risk of problem gambling, a rate higher than any other age category (AIHW 2023). Traditionally, commercial gambling was confined to physical machines or activities at appropriately licensed venues. However, there has been a significant increase in mobile gambling apps in recent years, supported by significant advertising across broadcast and digital media, and enabling a far greater permeation of gambling into everyday life in a range of settings.

Advertising on social media is an important pipeline for promoting gambling to young people. In our

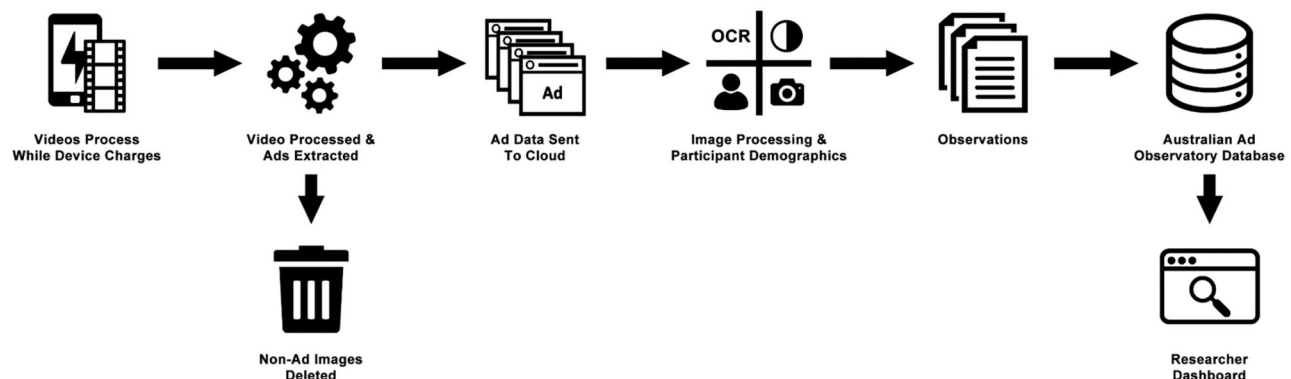


Figure 6. The Mobile Ad Toolkit.

study of gambling ads on Facebook, our provisional research findings have identified three important gambling ad issues in Australia. First, most gambling ads on Facebook are for “sports betting” from a limited number of legally compliant gambling providers. These ads may advertise gambling on specific events, may advertise an app or service, or may represent ads that seek to socialize gambling within the community by emphasizing the “thrill” of collaborative gambling with “mates.” Second, there is a small but significant amount of “gray zone” gambling ads that have an uncertain degree of compliance with Australian law. Some are clearly unlawful, yet circulated on Facebook, whereas others remain lawful yet target users with gambling-like systems without clearly identifying themselves as a gambling service. These types of ads mark out gambling as a surprisingly different kind of industry from those such as the alcohol industry. Alcohol advertising involves a physical commodity, whereas gambling is sold as a practice that can be provided from other territories. As such, gambling includes “micro” advertisers that seem to exist only for extremely short ad runs, and it is not neatly tied to a limited number of advertisers that can be approximated in advance. Gambling ads may directly link to gambling services in a separate app or website for immediate play—something that is functionally impossible with alcohol. All gray-zone ads target a small but quite vulnerable community and are likely designed not to trigger compliance checks when created on Facebook. Some of these ads are changed post-factum by the advertiser, and, in some cases, deleted by Facebook. Third, initial findings suggest that social media gambling ads work by identifying target users who are then subjected to gambling ad “bursts,” often related to when a user first logs in to social media. A *burst* is defined here as a sequence of ads shown to a user in one single browsing session, during which at least 50% of these ads tend to focus on one product or market segment. These ad bursts are hypothesized as representing as much as 70% of a user’s initial ad feed, overwhelming other kinds of advertising, suggesting that gambling ads are paid for as a premium to be prioritized over other types of advertising. These bursts may potentially lead to users taking on undue financial risks or to users developing, triggering, or relapsing an addiction.

The issue of the gambling ad burst is significant and requires further investigation because, unlike issues of advertising content, these bursts are contingent on the computational advertising model of the host platform, which remains hard to detect at scale

with many previous approaches. These bursts are hypothesized as occurring on or around login and may be related to the timing of social behavior (e.g., sports events or drinking); however, many existing methods only track the ad observation time and do not track user log-in times or location, nor do they capture mobile behavior, any of which could help confirm this hypothesis. Additionally, given that gambling ads have a significant focus on app-based gambling, it is likely that there are ads that will primarily appear on mobile, rather than desktop contexts.

The Mobile Ad Toolkit presents an opportunity to advance our work and confirm such hypotheses. Computational screen capture methods are likely to give us detailed insights about the frequency of gambling ads experienced by users when switching into or loading an app like Facebook and to confirm or complicate our understanding of these bursts. Whereas sequencing and timing is important for some classes of advertising (as discussed previously with respect to alcohol advertising and time of day/week), the ability for gambling providers to advertise and then facilitate problem gambling within the same mobile device at any time places a different emphasis on how people use their phones. Understanding whether gambling ads do indeed appear as bursts and identifying what triggers their appearance will be important for understanding how social media ad ecologies enable the targeting of users with potentially overwhelming volumes of gambling ads. Furthermore, if we can determine the key drivers for bursts of gambling ads and whether these lead to users following outbound links to gambling services, then we will be in a far better position to understand drivers of digital gambling behavior and intervene in systems that exploit or promote problem gambling.

Discussion and Future Considerations

In this article, we presented three complementary methods to observe digital platform advertising: (a) direct data gathering from ad transparency libraries; (b) participant data donation via a custom browser plugin; and (c) participant data donation through a mobile screen capture app. These methods are designed to extend existing ad data transparency initiatives currently offered by Meta and Google, enabling forms of observation that could facilitate advertising accountability by industry, regulators, researchers, and civil society. Although no single method alone solves the limitations of platform-provided transparency initiatives, we have designed this

suite of tools to address advertising observability across four key benchmarks, as illustrated in Table 1: first, enabling the systematic observation of ads published; second, collecting advertiser information and meta-data; third, assembling user demographic information associated with each ad; and fourth, observing patterns of ads as they unfold within social media feeds.

These four benchmarks—considered in order of observing ads, metadata, audience, and placement—articulate the shared interests of researchers, regulators, advertisers and civil society, respectively, in making the advertising model of digital platforms accountable to commercial and public stakeholders. Current transparency initiatives offered by Meta and Google limit data export and have few features available to probe advertising libraries in a meaningful manner. Using our methods, researchers and practitioners have been able to develop and apply a range of approaches to analyze the assembled datasets from descriptive statistics to detailed textual analysis. In the provided example of greenwashing, there is no population demographic data provided by any of the major ad transparency libraries, and hence no ability to systematically probe these libraries to collate examples of the demographic targeting of such advertising. By starting with a database of donated ads, however, researchers were able to develop a critical account of these advertising practices at scale, connected to important demographic data that is essential for ongoing regulatory efforts. These quantitative descriptions were also combined with detailed content analysis of these ads, from their use of specific color palettes through to language choices and choice of body types.

Beyond this single case study, most significantly these methods allow illustration of the unique patterns of advertisements that unfold in the individual feeds of users. The *custom browser plug-in* and *mobile screen recording apps* facilitate observation of the ad model

as it curates and orders advertisements, and the *white-list method* provides broader context of the advertisements observed within these patterns. For example, in the case of alcohol advertising in Australia, we have a mostly complete account of the volume and type of alcohol ads circulating on Meta’s ad network. We can track one advertiser to form a complete picture of all the ads they have active on the platform at a specific moment in time. The browser or mobile data donation frameworks then allow us to track these ads to see when and where they appear in user feeds, and what variations these users may encounter. Are these ads appearing early in the morning, or later in the day? What specific brands are seen by these users? And, in the future, what do users themselves feel about these ads and their placement in their news feeds?

Novel methods to study the new phase of “intelligent advertising” (Li 2019) are critical as personalization continues to erode the public observability of digital advertising and to participate more broadly in burdening users’ ecologies of attention within online platforms (Citton 2017). This type of research involves developing the infrastructure for observing the computational character of digital advertising itself. As illustrated with the previous examples, increasingly, we need to understand the patterns and placement of ads—not just their content. It is pertinent to consider if the user receiving the ad is attempting to limit their exposure to ads from this specific brand or advertiser category, and whether there are specific factors that they feel may make them more vulnerable to unwanted consumption (Borenstein and Taylor 2023)? To what extent do these computational ad models protect consumers and respect conscious choices on what products and services they wish to consume? For regulators, it should not only be a question of the ad contents, but also how, when, to whom, and in what context the ad is served.

Table 1. The three computational methods are complementary in terms of how they permit differing research agendas focused on exploration of targeted advertising.

Computational method	Are we able to observe the content of digital ads published on platforms?	Can we access advertiser information and meta-data?	Are we able to see the types of users targeted?	Can we observe patterns of ads as they unfold in user feeds?
Data gathering from transparency libraries	Yes	Yes, as published in the library	Partially, only for political and social issue campaigns	No
Custom browser plugin	Yes	Partially, by cross-referencing with transparency library	Yes, based on participant self-reported data	Partially, for Facebook in browser only
Mobile screen recording app	Yes	Only as visible in ad images, or if able to be linked with transparency library	Yes, based on participant self-reported data	Yes

The approaches to digital advertising observability we have developed move iteratively from observing ads in libraries to observing ads in the feeds of users. By placing emphasis on the algorithmic targeting and sequencing of ads, we aim to highlight the limitations of transparency libraries and the challenges of building techniques of meaningful observability of automated advertising without the cooperation of platforms. Our research demonstrates that it is technically possible to develop the approaches and tools to observe digital advertising. Of importance, whereas digital platforms can see these flows at scale, researchers, civil society, regulators and advertisers are unable to see them. Digital platforms have created a mode of advertising that, by historical standards, is uniquely unavailable to public scrutiny. Researchers, civil society, and advertisers have a shared interest in developing approaches to observability that would underpin more accountable forms of digital advertising (Yun and Strycharz 2023). At the center of the questions advertisers, civil society, and researchers have about how digital advertising works is the need to independently verify how its models of algorithmic sorting, targeting, and tuning operate “in the wild.”

This challenge becomes more acute as platforms continue to develop and deploy artificial intelligence tools in their ad models for data mining, analytics, and prediction, and increasingly also for creative asset generation (van Noort et al. 2020). These tools intensify personalization to a point where a single ad may only ever be seen by a single user. Observability will be an ongoing technical and political challenge in the relationships between digital platforms, the ad industry, regulators, researchers, and civil society (Campbell et al. 2022; Yun et al. 2020). By making all of underlying technology underpinning these methods open-source, we hope to stimulate further development and novel extension of this work to address these future concerns. Moreover, we argue for the centrality of data donation approaches whereby users choose to participate in and contribute to the practices of observing and making sense of the digital advertising that weaves throughout and potentially shapes their lives.

The research approaches for making digital advertising observable that we have developed set the foundation for collaboration between researchers across platform, media, and advertising domains. Researchers across these areas, together with regulators, civil society, and industry stakeholders, share a common interest in forms of observability that enable more accountability to public values, to consumer protections, and to

reliable market information. These forms of accountability will depend not just on the development of conceptual frameworks and techniques for observing digital advertising as a social process, but also the agreements, institutions, and settlements among stakeholders that underpin ensuring that advertising, as a form of communication that shapes public life and markets, is observable to society.

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No potential conflict of interest was reported by the author(s).

Note

1. Australian Internet browser market share data for 2022: <https://gs.statcounter.com/browser-market-share/desktop/australia/2022>.

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