The Effects of Online Advertising and Privacy Technologies on Consumer Purchase Behavior, Outcomes, and Satisfaction: A Registered Report

Consumer Relevance and Contribution Statement

Every day, billions of consumers navigate an online environment shaped by advertising that tracks their behavior and targets them with personalized messages. The extent to which this system helps consumers—by surfacing relevant products and lowering search costs—or harms them—by fostering annoyance, intrusion, and a sense of surveillance—remains one of the most consequential and open questions in the digital marketplace. Consumers increasingly respond by adopting ad-blockers and anti-tracking tools, while regulators debate sweeping privacy rules, yet the actual effects of these choices on consumers' own purchasing behavior, spending, and satisfaction are poorly understood.

This registered report addresses that gap. Existing evidence is fragmented: firm-centric studies emphasize clicks and conversions, observational data cannot cleanly isolate causal effects, lab studies miss real-world validity, and platform experiments cannot follow consumers across the open web. As a result, competing theories about advertising's role—informative, persuasive, or peripheral—remain untested at the level of the consumer.

We contribute a large-scale, ecosystem-wide, longitudinal field experiment that randomly assigns consumers to targeted ads, anti-tracking, or ad-blocking conditions, then measures their actual browsing and purchasing across websites, platforms, and devices over three months. This design makes three contributions. First, it shifts the focus from advertisers and publishers to consumers themselves—their purchases, prices paid, and satisfaction. Second, it addresses prior methodological limits by enforcing treatments and tracking behavior across the entire online ecosystem rather than a single platform. Third, it separates the effect of advertising's mere presence from the incremental effect of behavioral targeting.

By pre-registering competing theories and a rigorous analysis plan, the study delivers causal evidence—whatever the direction of results—on how exposure to, or protection from, online tracking and advertising shapes consumer welfare, directly informing consumers, marketers, and policymakers.

ABSTRACT

The online advertising ecosystem's reliance on consumer behavioral tracking creates an intense, unresolved debate over the impact of online ads on consumer shopping behavior, outcomes, and satisfaction. Existing empirical work has been helpful, but identifying the causal effects of ad exposure separately from behavioral targeting across the advertising ecosystem, and the potential impact of privacy technologies on that ecosystem, presents methodological challenges. This Registered Report presents a large-scale, ecosystem-wide, randomized, three-condition longitudinal field experiment. Participants are assigned to (1) Targeted Ads, (2) Anti-tracking, or (3) Ad-blocking conditions, and both observational and survey data are collected over a three month period. This design estimates the incremental effect of targeting and allows for a causal test of three competing macro-theories that predate the digital age: the Informative Engine (Nelson 1974), the Market-Shuffling and User Experience Engine (Dixit and Norman 1978), and the Complementary View/Peripheral Influence Engine (Hansen and Christensen 2003). This field experiment provides an ecosystem-wide assessment of the causal impact of online advertising on consumer purchasing behavior, outcomes, and satisfaction.

Keywords: Online advertising; Behavioral advertising; Field experiments; Online tracking; Privacy

1. INTRODUCTION

The modern online economy relies on a multi-billion-dollar advertising ecosystem that monetizes consumer attention and data, creating a complex and often debated set of trade-offs for users, firms, and regulators (Acquisti 2024; Choi et al. 2020; Decarolis and Rovigatti 2021; Gordon et al. 2021; Marotta et al. 2022). Industry stakeholders champion the modern advertising model, asserting that extensive consumer tracking and behavioral targeting lead to mutual benefits: consumers enjoy greater content relevance and lower search costs, advertisers gain efficiency in reaching target audiences, and publishers are able to subsidize "free" content and services (Beales 2010; Brynjolfsson et al. 2025; Farahat and Bailey 2012; Peukert et al. 2022; Shiller, Waldfogel, and Ryan 2018). This perspective is often supported by firm-centric data demonstrating the high effectiveness of targeting on metrics such as click-through rates (CTR) and conversions (e.g., Bleier and Eisenbeiss 2015; Farahat and Bailey 2012; Gordon et al. 2019; Gordon, Moakler, and Zettelmeyer 2023; Huang and Xue 2025; Sahni, Narayanan, and Kalyanaram 2019; for a review, see Choi et al. 2020).

In contrast, some researchers, consumer groups, and policymakers have voiced concern over negative externalities. These include the psychological impact of constant surveillance—feelings of creepiness, annoyance, and intrusion (De Keyzer, van Noort, and Kruikemeier 2022; Lee and Rha 2016; Moore et al. 2015; Ur et al. 2012)—as well as the potential for behavioral manipulation or the risks of promoting online addiction (Allcott, Gentzkow, and Song 2022; Aridor et al. 2024). Recent scholarship highlights critical frictions in this ecosystem, ranging from the welfare implications of choice architecture in data sharing (Farronato et al. 2025) to the detrimental effects of toxic content on user engagement (Beknazar-Yuzbashev et al. 2025a). This backlash is evident in the widespread adoption of privacy tools, such as ad-blockers and anti-tracking tools, as well as waves of stringent legislation such as the General Data Protection Regulation (GDPR), the Digital Services Act, and the California

Consumer Privacy Act (CCPA) (e.g., Peukert et al. 2022; Wang, Jiang, and Yang 2024). Furthermore, technology firms like Apple have incorporated in their operating systems privacy protections to limit tracking (e.g., Aridor et al. 2025; Cheyre et al. 2025), and others—like Google with the recently abandoned "Topics"—have experimented with approaches to increase privacy protection while preserving the ability to target consumers with personalized ads (Google 2022). The enactment of privacy regulations and the growing popularity of ad-blockers and anti-tracking measures, on the other hand, have been met with concern. Research highlights that tools like ad-blockers can pose a threat to the ad-supported web by reducing publishers' revenues (Shiller et al. 2018) and can potentially harm consumer welfare by limiting the discovery of relevant products (Brynjolfsson et al. 2025). When the Federal Trade Commission sought feedback on "commercial surveillance," many organizations defended behavioral advertising by touting its economic advantages for all parties in the ecosystem, including the consumers (Federal Trade Commission 2022).

Despite these debates, scholarly efforts to measure and disentangle the impacts of online tracking, targeting, and advertising on consumer outcomes are relatively few. Much of the expansive body of work in economics, marketing, and information systems on online advertising has tended to evaluate the advertising economy from a firm-centric perspective, focusing on its impact on advertisers, networks, or publishers, with a heavy emphasis on the effectiveness of a set of specific advertising campaigns, and often mapping the relationships between online ads, click-through rates, and conversion metrics (Bleier and Eisenbeiss 2015; Farahat and Bailey 2012; Ghose and Todri-Adamopoulos 2016; Lewis, Rao, and Reiley 2015; Manchanda et al. 2006; Rutz and Bucklin 2012; Sahni 2015; Schwartz, Bradlow, and Fader 2017; Wang et al. 2024; Wernerfelt et al. 2025). While some scholarship explores the posterior effects of viewed-but-not-clicked ads (Ghose and Todri-Adamopoulos 2016), work centered specifically on the consumer side (such as consumer purchases, satisfaction, and long-term behavior in response to targeted advertising) remains comparatively scarce and is limited by existing methodologies. Much of the literature under this stream relies either on observational data (e.g., Beales 2010), which does not permit clean causal identification; or platform-specific experiments (e.g., within Google or Meta), which are not designed to capture the holistic consumer journey outside those platforms and across the open web (e.g., Brynjolfsson et al. 2025); or survey-based experiments (e.g., Mustri et al. 2023; Lin, Cheyre, and Acquisti 2023), which do not capture actual purchase behavior. Similarly, existing literature on the adoption of privacy tools that may curtail tracking, targeting, or ads (such as ad-blockers) has tended to focus on supply-side risks, such as publisher revenue loss and content quality degradation (e.g., Shiller et al. 2018). Only limited research has examined the effect of ad-blockers on consumer outcomes, and this literature has relied either on large-scale observational data (Todri 2022; Yan, Miller, and Skiera 2022), which offer real-world scale but generally limit causal identification, or laboratory studies (Frik et al. 2020), which provide control but often lack the ecological validity and temporal depth necessary to understand real-world shopping behavior. Finally, research-driven platforms (such as consumer-monitoring extensions and apps) for analyzing digital behavior have emerged in recent years (e.g., Farronato et al. 2024; Reeves et al. 2021), but do not focus on manipulating exposure to or protection from online tracking, targeting, and advertising.

Our approach complements existing literature on online advertising, related privacy technologies, and consumer outcomes, by utilizing an experimental infrastructure we have recently developed (Anonymized Authors 2026).[1] The novel infrastructure enables randomized, Internet ecosystem-wide, multi-platform, multi-device marketing interventions, while monitoring real-time participants' compliance and cross-device activity. We leverage this infrastructure to conduct a randomized, large-scale, longitudinal field experiment designed to causally estimate the effects of the

[1] Anonymized Authors (2026) is provided as a companion document in the Appendix of this Registered Report submission.

online advertising ecosystem, and **capture the effects of exposure to, and protection from, online tracking, targeting, and advertising on consumer purchase behavior, outcomes, and satisfaction**.

The infrastructure relies on study software that consenting participants install and keep on their devices for the duration of the experiment. The software consists of a browser extension that participants install on their computers and that records numerous metrics (including participants' browsing behaviors, advertising exposure, and online purchases); a mobile phone component that records browsing behavior on mobile devices; and an email client that detects promotional emails and online purchase confirmations received by the participant. The software remotely exerts ad-blocking and anti-tracking manipulations on both computer and mobile devices. During the experiment, we plan to monitor 1,200 participants' online behaviors longitudinally for three months. A randomized three-condition design uses treatment bundles to allow for a causal decomposition of advertising's effects: Targeted Ads (ads are shown, and are likely to be behaviorally targeted, because participants can be tracked by advertising networks), Anti-tracking (ads are shown, but are significantly less likely to be behaviorally targeted, as the study software opts participants out of ad personalization across major platforms and advertising networks), and Ad-blocking (ads are minimized, as they are blocked to the greatest extent possible by current ad-blocking technology). This approach moves beyond the simple "ad/no-ad" dichotomy to measure the incremental role of behavioral targeting on consumer purchases, outcomes and satisfaction.

We contribute to prior works in three ways. First, we focus on the impact of the online advertising ecosystem on consumers rather than advertisers or publishers. In particular, we analyze how the presence of ads or targeting of those ads (or, conversely, the presence of anti-tracking or ad-blocking technologies) influence users' purchase behavior, and ultimately purchase outcomes (such as amounts spent, prices paid), and satisfaction. Second, we address prior methodological challenges by employing an ecosystem-wide longitudinal field methodology that both enforces treatments and tracks consumers' behaviors across websites and platforms, as well as on both desktop and mobile devices. Third, our randomized three-condition design allows us to compare the relative impact of tracking, targeting, ad-blocking, and anti-tracking technologies on consumers' behavior and economic outcomes.

The experiment is designed to provide internally valid causal evidence for a clearly defined population and technological setting: U.S.-based online shoppers who use Chrome on Windows, do not currently use ad-blocking or anti-tracking tools, and are willing to participate in a longitudinal research panel involving passive measurement of online activity. This scope reflects the technical requirements of implementing and verifying the experimental treatments across participants' devices, as well as the need to estimate the effects of adopting advertising and privacy tools among consumers for whom such adoption represents a change from their current or usual browsing environment. Therefore this design does not represent all internet users or all technological contexts. However, it captures a large and substantively important segment of online consumers and enables a level of causal identification and ecosystem-wide cross-platform measurement that is difficult to obtain with observational data, laboratory experiments, or single-platform field studies. By pre-specifying the competing theoretical frameworks, hypotheses, and a comprehensive data analysis plan in this Stage 1 Registered Report, we aim to offer a contribution to one of the most pressing consumer debates of our time: how exposure to—or protection from—online tracking, targeting, and advertising affects consumers' online shopping.

2. CONCEPTUAL FRAMEWORK AND RELATED LITERATURE

An extensive literature has examined the role of advertising and attempted to quantify its effects on firms, publishers, and consumers. In this section we first outline three competing conceptual views of how advertising shapes consumer behavior specifically. We then review empirical evidence bearing on these views and explain why existing approaches—relying on observational data or platform-specific experiments—are not enough to disentangle the effects of advertising presence on consumers from those of behavioral targeting, leaving these competing theories unresolved and motivating the need for a different empirical approach.

Three Conceptual Views of Advertising

Theories regarding the function of advertising and its effect on consumer choice predate the digital age but are highly relevant to understanding the impact of online advertising, as well as of technologies (such as ad-blockers and anti-tracking tools) that curtail it. Within this domain, three classic, often competing, views have emerged.

The **informative view** posits that advertising's primary role is to reduce consumer search costs by communicating a product's existence, attributes, price, or location (Nelson 1974). This view suggests that advertising provides value to consumers by making the shopping process more efficient. In the context of online advertising, behaviorally targeted ads are examples of marketing efforts that may reduce consumer search costs, and increase their welfare, by using information collected about consumers to present them with ads for products they are more likely to be interested in (Beales, 2010). A challenge to this theory is that information provided by an interested party may be biased in the advertiser's favor (Marotta et al. 2022).

The opposing **persuasive view** suggests that ads aim to shift consumers' preferences to increase a product's demand at the expense of market efficiency (Dixit and Norman 1978). Under this lens, rather than facilitating discovery, digital advertising aims to shape consumers' preferences by creating perceived needs and steering demand toward advertised products. In digital environments, pervasive tracking and highly targeted formats may amplify these persuasive forces (Moradi, Cheyre, and Acquisti 2025; Mustri et al. 2023). In contrast to the informative view, the persuasive view implies that advertising may increase search cost when ads are perceived as annoying, distracting, and privacy intrusive, thus degrading the overall quality of the browsing experience, and potentially suppressing commerce that would have otherwise occurred in a cleaner environment.

A third view presents advertising's role as **complementary or peripheral** (Hansen and Christensen 2003). Under this view, advertising affects demand not by distorting preferences, but by effectively becoming an inherent attribute of the advertised product, thereby building valuable brand equity (e.g., the prestige associated with luxury goods). Complementary advertising does not necessarily influence consumer search costs, but it does influence the utility the consumer gets from the good consumption.

Existing Evidence on the Effects of Online Advertising on Consumer Purchases

The body of research on online advertising is vast; a subset of it has focused on the effect of online ads on consumer purchases. To understand that effect, it is essential to trace the consumer's journey from initial ad exposure through to a final purchase decision (Kannan and Li 2017). Though the existing literature provides evidence on the effectiveness of advertising at isolated stages—such as brand awareness or initial engagement (Batra and Keller 2016)—a critical examination reveals that the link between an initial ad interaction and a final purchase is complex and tenuous (Danaher and van Heerde 2018; Lewis and Rao 2015).

Studies examining the link between ad exposure and immediate actions, such as clicks, suggest that targeting—either contextual (ads aligned with current webpage content) or behavioral (ads based on past browsing history and profile data)—is highly effective. A significant body of research demonstrates that behavioral targeting is associated with higher click-through rates (CTR); for example, targeting has been found to increase CTR by as much as 67% (Farahat and Bailey 2012). The perceived value of this precision is reflected in the market price, as advertisers pay considerably more for targeted impressions (Beales 2010). Recent studies have estimated how privacy interventions such as personal data regulations restricting targeting can affect advertising effectiveness, frequently documenting substantial negative effects (Goldberg, Johnson, and Shriver 2024; Aridor et al. 2025). However, these studies face the challenge of separating declines in advertising effectiveness from measurement challenges caused by the regulations themselves, or focus on platforms and vendors that disproportionately depend on behavioral targeting for customer acquisition.

The practical significance of the direct effects of advertising exposure has been contested in the literature. While targeting clearly influences advertising clicks and stated purchase intent, it is harder to establish whether it produces a genuine lift in consumer interest. Lewis et al. (2015) showed that the majority of sales lifted by a display ad campaign came from consumers who merely *viewed* the ads, never clicked, and made the purchase offline. And much like sponsored search results on Google, users may click on targeted ads simply because they appear first on the page or align with a search they were already conducting, rather than because the ad itself generated a lift in interest for the advertised product. Additionally, Ursu, Simonov, and An (2025) find that ad-driven visits constitute a meaningful share of traffic but tend to be shorter, less exploratory, and less likely to convert, challenging the use of clicks as a reliable indicator of impact. Taken together, these findings provide a critique of the simplistic sales funnel model. The research suggests that a click is neither a necessary nor sufficient condition for a sale. This complexity in turn suggests that the effect of advertising can be more nuanced than immediate measures of transactional intent typically capture, and underscores the need to examine how consumers' cumulative exposure to tracking and targeted advertising—or their being shielded from it—shapes their purchasing behavior, marketplace experiences, and downstream purchase outcomes.

Evidence from Studies on Ad-Blocking and Anti-Tracking

Research examining the effects of ad-blocking has traditionally focused on the perspective of publishers and the advertising industry. Industry data has estimated substantial revenue losses—billions of dollars—due to the use of ad-blockers, leading the Interactive Advertising Bureau (IAB) to characterize them as an existential threat to their business model (Sullivan 2017). From the publisher's perspective, studies have confirmed that ad-blocking reduces site visits and curtails revenue (Shiller et al. 2018).

Economic and marketing research on ad-blocking from the consumer's side is sparse. An observational work by Miroglio et al. (2018) suggests that users of ad-blockers spend more time browsing online content. In addition, using data from a news website, Yan et al. (2022) find that ad-blocker adoption increases the number of articles and the variety of articles users consume on the website, implying that ad removal improves engagement and overall experience. Other studies provide conflicting evidence regarding the impact on consumer expenditure, ranging from a reduction in spending (Todri 2022), to no significant effect on economic outcomes in a controlled setting (Frik et al. 2020), and even increases in online purchases (Suárez and García-Mariñoso 2021).

Previous research has studied the effect of tracking in terms of ad personalization and found a positive effect of tracking on ad effectiveness (for a review, see Yeo, Chu, and Li 2025). With regard to the effect of anti-tracking, recent work has studied some of the economic impacts of privacy regulations (such as the General Data Protection Regulation) or privacy industry initiatives (such as Apple's ATT) which reduce consumer tracking and targeting (Goldberg et al. 2024; Aridor et al. 2025), but this stream of research has mostly focused on the impact of privacy initiatives on advertisers or publishers' revenues. Limited attention has been paid to the impact of installing anti-tracking technologies on consumers, including shopping behaviors, outcomes, and satisfaction.

Methodological Approaches in Current Literature

As mentioned in prior sections, in recent years some of the research on online advertising has started focusing on its impact on consumers. This is an undeniably positive trend. But the extent to which one can derive firm conclusions on the effects of the online advertising ecosystem on consumer purchase behavior, outcomes, and satisfaction is affected by methodological hurdles.

A large portion of this body of work has relied on observational data, such as browser histories or datasets provided by industry partners (e.g., Aridor, Che, and Salz 2023; Goldberg et al. 2024). This methodological approach offers high statistical power. However, this methodology can suffer from self-selection biases and limited causal identification. For instance, consumers who choose to use privacy tools (such as ad-blockers or settings and extensions that shield the consumer from tracking and targeting) may be likely to differ systematically from those who do not, making it difficult to isolate the actual effect of the advertising ecosystem from underlying user characteristics.

Laboratory experiments and survey-based methods offer high levels of control and deep insight into consumer attitudes (Mustri et al. 2023; Ur et al. 2012). However, these studies often lack ecological validity and temporal depth. They cannot replicate the complexity, duration, or naturalistic environment of real-world online experiences, where consumers browse, shop, and search over extended periods.

Field experiments conducted within the "walled gardens" of specific platforms like Google, Amazon, or Facebook (Brynjolfsson et al. 2025; Sahni et al. 2019) benefit from large samples and randomization, providing strong internal validity. However, they are inherently platform-specific: they can estimate advertising effects within a single platform, but cannot observe the broader consumer journey across the open web. For instance, they may miss cross-platform spillovers, such as whether changes in ad exposure or purchasing on one platform affect subsequent search, purchasing, or other outcomes elsewhere.

Finally, recent studies use consumer-centric data and infrastructures to analyze digital behavior (Farronato et al. 2024) and personal life experiences (Reeves et al. 2021). Independent academic infrastructure projects, such as Webmunk (Farronato et al. 2024) and those summarized in Aridor et al. (2024), enable broad cross-platform data collection and experimental manipulation (e.g., modifying page elements or restricting app access). However, those infrastructure currently do not focus on ads, and do not manipulate exposure to, or protection from, tracking, targeting, and advertising across devices and online services. The infrastructure underlying the experiment presented in this Registered Report complements and advances this prior literature. It provides a large-scale, ecosystem-wide, longitudinal field experimental tool with random assignments to causally identify the effect of the modern advertising ecosystem on consumer purchase behavior, outcomes, and satisfaction.

3. EXPERIMENTAL INFRASTRUCTURE

This Registered Report presents the design of a longitudinal field experiment on the effect of online advertising on consumers. The experiment leverages an infrastructure recently developed to study the impact of exposure to, or protection from, online tracking, ad targeting, and advertising, on consumer purchase behavior, outcomes, and satisfaction (Anonymized Authors, 2026). A high-level view of the infrastructure is summarized in the rest of this section (Section 3), to provide context for the hypothesis development (Section 4). Details about the experimental design are presented in Section 5. Section 6 presents our data analysis plan. Limitations are discussed in Section 7. Additional technical details about the infrastructure, its features, the iterative testing it underwent, and so forth, are discussed in Anonymized Authors (2026), key portions of which are provided as a companion document (Appendix) of this Registered Report submission, in order to allow reviewers to evaluate the experimental infrastructure underlying the proposed report.

The infrastructure is based on a client-server architecture: the client is installed by consenting, fully-informed participants on their devices, and it transmits a vast array of telemetry data from the participants' devices to the servers, where it is stored and analyzed. The client comprises the study software (currently designed for Windows computers), which includes a computer browser extension (currently designed for Chrome and Chromium devices), an email client, and mobile phone components (for both iOS and Android). The study software and its various components have two functions: 1) collecting participants' data across devices, and 2) exerting the experimental conditions, also across devices. The study software also fulfills additional secondary functions, including verifying and maintaining participants' compliance with the experimental hypotheses, enforcing multiple de-identification and privacy-preserving steps to protect participants' data confidentiality, and detecting and removing potential malicious users (such as bots or scammers). See additional technical details in Appendices A and B of the companion document.

Collecting Participants Data

The computer browser extension records a vast array of metrics, including all URLs visited by the participant on their computer using that browser, with associated timestamps and user behaviors (clicks);[2] the entire HTML pages of a select portion of URLs visited (including: merchant sites; search engine sites; LLM sites); metadata and screenshots of all ads displayed on the browser; cookies and local storage data; and more. The mobile phone component collects URLs visited on Safari by iOS users, and on Chrome by iOS or Android users. The email client detects promotional/marketing emails and purchase confirmation emails received by the participant, regardless of what email account, provider, or software the participant uses (e.g., gmail or yahoo mail, accessed via Outlook or via a web browser, and so forth). The study software uses a combination of rule-based pattern matching and adaptive updating to locally identify a participant's personal identifying information (PII) in both email and browsing data, and remove it before any data is sent to the servers.

[2] For a pre-specified set of sensitive services—such as webmail, cloud document and storage services, online banking, and government websites—for privacy reasons the software records only truncated URLs (e.g.: https://docs.google.com/) together with timing and duration of the visit. No page-level data (such as HTML, ads, or cookies) is collected (see Appendix A of the companion document).

Of specific interest to this Registered Report, the collection of data captured across the components (URLs and HTML pages from sites the participants visited on their computer browsers; URLs visited on their mobile phones; promotional and shopping confirmation emails received on their email account) permits an in-depth reconstruction of the purchase behavior and associated purchase outcomes for each participant. For instance, the infrastructure can identify: merchant sites visited; products searched, advertised, or seen on a merchant's page, and ultimately purchased; prices paid; ads seen on any visited page; and so forth. Data captured directly from participants' devices is complemented by self-reported data collected via surveys regularly administered at entry, during the experiment, and at exit. The surveys include questions related to participants' satisfaction with browsing, shopping, searching, and so forth. This Registered Report utilizes a subset of the data collected by the experimental infrastructure, as detailed in Section 5 and in the draft preregistration document that has also been provided to the reviewers as part of this Registered Report submission.

Exerting Experimental Conditions

The study software allows the exertion of the experimental conditions. Exertion is automated and remotely executed on the participant's computer; on the participant's mobile device, exertion requires the participants to follow simple instructions; compliance with those instructions is monitored by the infrastructure. The experimental conditions are designed to causally separate the effects of advertising presence from those of behavioral targeting—an empirical distinction that has been largely inaccessible in prior work:[3]

1. **Targeted Ads:** Participants are exposed to ads (including display ads, sponsored search ads, Facebook ads, YouTube video and static ads, and so forth) and experience ad targeting as it is the

[3] Beknazar-Yuzbashev et al. (2025b) examine the distinct roles of ad volume and microtargeting on user behavior on Facebook. Their study primarily focuses on user engagement dynamics within social media environments, rather than cross-device, ecosystem-wide ecommerce purchase tracking.

common online default. Ads displayed to these participants are, or can be informed, by their individual-level activity across websites and platforms—therefore, many of them are likely to be behaviorally targeted. To ensure condition cohesion, automated scripts verify that participants are opted-in to tracking and targeting across their devices, and if their state differs, automatically opt them in to ad targeting accordingly on desktop, or provide instructions to correct their settings on mobile. To achieve that goal, the study software implements a treatment bundle that leverages a combination of industry self-regulatory tools (Digital Advertising Alliance 2009) including opt-out cookies, Facebook/Meta settings, Google account settings, and several Chrome settings (technical details are available in Appendix A of the companion document).

2. **Anti-tracking:** Participants are opted-out of tracking and targeted advertising across their devices using the same combination of industry self-regulatory tools discussed above, which are automatically set to minimize online tracking and ad targeting. In this condition, participants see ads (including display ads, sponsored search ads, Facebook ads, YouTube video and static ads, and so forth), but those ads are less likely to be informed by individual-level tracking data, and thus are less likely to be behaviorally targeted. This condition corresponds to a consumer who comprehensively leverages available online tools to limit behavioral tracking for advertising purposes, but are still exposed to ads (including contextually targeted ads).

3. **Ad-blocking:** The infrastructure leverages state-of-the-art ad-blocking tools. In this condition, participants' exposure to ads (including display ads, sponsored search ads, Facebook ads, YouTube video and static ads, and so forth) is minimized to the greatest extent made possible by a bundle of commonly used current ad-blocking technologies.

We operationalize the experimental conditions through multi-component treatment bundles rather than through single, isolated interventions. This choice reflects the practical reality that consumers typically encounter advertising and privacy technologies as configurations of tools that jointly shape the browsing experience. The design generates experimental variation in advertising exposure and behavioral targeting while maintaining a realistic representation of how such tools are experienced by consumers. The main intended effect of the bundles is to change participants' exposure to tracking, behavioral targeting, and advertising. At the same time, as would occur outside the experimental setting, these tools can influence other features of web use, including loading speed and the functionality of certain sites. For this reason, the terms Targeted Ads, Anti-tracking, and Ad-blocking refer to randomized assignment to these broader intervention packages.

The intended performance of the experimental treatments was confirmed in numerous pilots and internal tests conducted prior to launch (see Appendix C of the companion document). The infrastructure is regularly tested and maintained across the lifetime of the experiment to ensure the continued accuracy of its data collection and the continued effectiveness of the treatment bundles.

Objectives and Features of the Infrastructure

The experimental infrastructure summarized above is designed to advance current experimental work on the impact of online advertising on consumer purchase behavior. By recording real user behaviors in naturalistic settings, over an extended period, across devices, and across any platforms the participant may visit or interact with through their browsers, the infrastructure offers a rigorous approach for inquiries into consumer purchase behavior, outcomes, and satisfaction. By exogenously exerting experimental treatments also across devices and platforms, the infrastructure is capable of providing novel insights on the competing conceptual views we outlined in previous sections.

4. HYPOTHESES

The Impact on Consumer Purchase Behavior

Extant research has produced differing findings on the effect of ad-blocking on consumer spending. This tension in the literature supports three mutually exclusive macro-theories of consumer behavior regarding the impact of advertising on purchasing: the Informative Engine (Theoretical logic 1), the Market-Shuffling and User Experience Engine (Theoretical logic 2), and the Complementary View or the Peripheral Influence Engine (Theoretical logic 3). These theories of advertising predate today's digital ecosystem, in which consumers face continuous cross-platform exposure and targeting based on granular behavioral data. And existing evidence of the impact of online advertising on shopping behavior remains fragmented across observational studies, individual campaigns, and platform-specific experiments. The experimental infrastructure underlying this Registered Report offers a new way to differentiate among informative, persuasive or market-shuffling, and complementary or peripheral accounts: its ecosystem-level intervention separates advertising exposure from behavioral targeting, while its wide-angle measurement follows consumers from ad exposure through search, purchase, and post-purchase evaluation.

Theoretical Logic 1: The Informative Engine

This logic posits that advertising is a potent force amplified by behavioral targeting. It is supported by studies finding that ad-blocker adoption can decrease online spending (e.g., Todri 2022). Such type of finding, although observational, suggests that removing ads and tracking removes a stimulus that drives commerce.

Recent evidence from the rollout of Apple's App Tracking Transparency (ATT) policy may provide some indirect support for this logic. By limiting the ability of platforms like Meta to track users across apps, ATT degraded the core mechanism of behavioral targeting. The result was a substantial and negative impact on revenues for some firms, with studies documenting declines between 8-40% for small firms that were highly dependent on Meta's advertising ecosystem for customer acquisition (Aridor et al. 2025). While these effects are dramatic, however, their aggregate impact is unclear, as it is unknown how representative of the broader economy are firms that depend primarily on Meta for product promotion , or whether other firms are similarly affected.

Notwithstanding these concerns, the literature suggests that advertising as an informative engine can facilitate product discovery and can drive economic activities for some firms. Therefore, systematically dismantling this engine in our experiment may have a direct, negative impact on consumer purchasing. According to this logic, the Ad-blocking condition, by removing the stimulus almost entirely, should result in the lowest level of purchasing. The Anti-tracking condition, by removing the informative targeting layer but leaving less effective contextual ads, should produce an intermediate outcome. The Targeted ads condition, representing the full power of the advertising-as-an-informative-engine ecosystem, should yield the highest level of purchasing.

Hypothesis 1a: *Purchase activity (total expenditure, purchase frequency[4]) will be highest in the Targeted Ads condition, significantly lower in the Anti-tracking condition, and lowest in the Ad-blocking condition (Targeted Ads > Anti-tracking > Ad-blocking).*

Theoretical Logic 2: The Market-Shuffling and User Experience Engine

The persuasive view of advertising suggests that advertising can artificially shift consumer preferences to increase a product's demand, but much of this gain is a business-stealing effect that reshuffles market shares without increasing total social demand (Dixit and Norman 1978). If many firms utilize granular targeting to persuasively shift market share, the resulting increase in ad density and privacy-intrusiveness may lead to negative experiential costs. As firms compete for attention through

[4] It is possible that these variables may not move in the same direction. For simplicity, we derived the hypotheses from the macro-theory. For example, the informative engine theory suggests that advertising facilitates purchase frequency, but does not comment on the price consumers pay. Thus, it is plausible that the total spending is higher, the same or even lower depending on the price consumers pay. We will analyze the mechanisms in detail if the variables move in different directions.

increasingly aggressive targeting, the collective result is an increase in consumer friction—annoyance and distraction—that ultimately suppresses total commerce. This view is supported by findings that ad-blocker use may lead to an increasing online browsing of news content (Yan et al. 2022) or even an increase in online purchases (e.g., Suárez and García-Mariñoso 2021), implying a cleaner, faster browsing environment fosters more shopping.

This logic questions the true demand-generating power of ad targeting. The observed lift from targeted ads in some studies may be inflated by selection bias; advertisers target users who already have a high baseline probability of purchasing, making it difficult to disentangle the ad's true causal effect (Lambrecht and Tucker 2013). More critically, this logic focuses on the direct utility or disutility of the browsing experience itself. Online ads are a well-documented source of frustration for some consumers. They are often perceived as annoying, distracting, and intrusive, degrading the overall quality of the user experience (Goldstein et al. 2014). By eliminating this source of friction, ad-blockers may create a cleaner, faster, and more pleasant browsing environment. This superior experience may lead to increased online engagement, more time spent browsing and shopping, and ultimately, more purchasing. In this view, the presence of ads (both targeted and non-targeted) suppresses purchasing.

Hypothesis 1b: *Purchase activity (total expenditure, purchase frequency) will be highest in the Ad-blocking condition, and significantly lower and not significantly different from each other in the Targeted Ads and Anti-tracking conditions (Ad-blocking > Targeted Ads ≈ Anti-tracking).*

Theoretical Logic 3: The Peripheral Influence Engine

This view posits that, for most purchases, display advertising is a weak and peripheral force. This suggests core purchasing is driven by intrinsic needs, making ad presence or absence largely irrelevant to aggregate outcomes.

Several streams of evidence support this view. First, the phenomenon of "banner blindness" is well-documented: consumers have learned to unconsciously ignore content in areas of a webpage where ads typically appear, rendering many impressions functionally invisible (Benway and Lane 1998; Zambarbieri et al. 2008). Consumers also actively engage in ad avoidance across various media, not just online (Cho and Cheon 2004). Second, controlled laboratory experiments such as Frik et al. (2020) may provide some precedent for a null finding. In Frik et al. (2020), blocking contextual ads in search results had no statistically significant effect on the prices of products participants chose to purchase, the time they spent searching, or their satisfaction with the outcomes. Furthermore, a recent, large-scale, and long-term field study may provide corroborating evidence for this perspective. Brynjolfsson et al. (2025) exploited a natural experiment on Facebook's A/B testing platform to compare the willingness-to-pay of users exposed to the normal ad-supported platform versus a holdout group that saw no ads for years. Using incentive-compatible choice experiments, they found no significant difference in users' willingness-to-pay to use Facebook between the two groups, suggesting that the perceived net utility impact of the entire advertising apparatus on the platform may be close to zero for the average consumer. In short, this logic suggests that neither removing targeting nor removing ads altogether will meaningfully alter aggregate purchase behaviors.

Hypothesis 1c: *There will be no significant difference in purchase activity (total expenditure, purchase frequency) across the three experimental conditions (Targeted Ads = Anti-tracking = Ad-blocking).*

The tension in the existing literature—where some observational and firm-level data suggests a large economic impact of advertising, while some experimental and consumer-level data suggest a null effect—points to a potential disconnect between firm revenue and aggregated consumer outcomes. It is plausible that advertising is effective at persuading a subset of consumers to purchase, thereby driving firm revenue, while simultaneously creating disutility for a broader set of consumers through a degraded user experience. This could result in a net-zero effect when averaged across the population. The primary economic effect of advertising in this scenario may be a reallocation of spending across consumers and firms, rather than the creation of substantial new value for consumers. Our experiment, by measuring both economic outcomes (spending) and subjective outcomes (satisfaction) via random assignment, is uniquely positioned to investigate this possibility.

The Impact on Consumer Satisfaction

Consumer shopping behavior and outcomes are not solely an economic calculation; they also encompass subjective experiences. We assess this dimension through two distinct measures: satisfaction with purchases made (the outcome) and satisfaction with the overall online browsing experience (the process). This distinction is critical, as it is plausible that advertising can simultaneously increase one while decreasing the other—a trade-off that has been under-explored in the literature. Purchase satisfaction is traditionally defined using the expectancy disconfirmation framework (Oliver 1997) as a post-consumption evaluative judgment that occurs when a consumer compares the actual performance of a purchased product or service against their prior expectations. Browsing satisfaction focuses on the pre-purchase or non-purchase stage of the consumer experience, intended as a global affective and cognitive evaluation of the store or website environment during data gathering and exploration, independent of a final transaction (McKinney, Yoon and Zahedi 2002) . The industry often argues that the relevance from targeting improves the overall experience (Deloitte Digital 2024), while consumers frequently report that ads are annoying, intrusive, and “creepy,” degrading the experience (De Keyzer et al. 2022). These are not mutually exclusive claims. A targeted ad could successfully lead a consumer to a product they love (high purchase satisfaction) while the process of being shown that ad and others was irritating (low browsing satisfaction). The overall implications for consumer outcomes may therefore depend on how consumers balance improvements in purchase satisfaction against changes in browsing experience.

Theoretical Logic 1: The Precision-Friction Engine

This logic posits that different components of the advertising ecosystem provide distinct forms of value and cost, leading to nuanced and potentially conflicting patterns of satisfaction outcomes. It suggests a trade-off between the quality of purchase outcomes and the quality of the browsing process.

On the one hand, relevant, personalized advertising can lead to the discovery of better-matched products, increasing the utility derived from the purchase itself. If a targeted ad helps a consumer find a product that perfectly suits their needs, their satisfaction with that purchase should be higher. This would predict the highest purchase satisfaction in the Targeted Ads condition, where personalization is maximized.

On the other hand, the process of being exposed to ads itself is a source of disutility. Ads are often considered annoying, intrusive, and disruptive (Ur et al. 2012). Removing them may create a faster, cleaner, and more pleasant online environment. This would predict that satisfaction with the browsing experience will be highest in the Ad-blocking condition, where these irritants are absent (Miroglio et al. 2018).

Hypothesis 2a: *Purchase satisfaction will be highest in the Targeted Ads condition and lowest in the Ad-blocking condition (Targeted Ads > Anti-tracking > Ad-blocking). Conversely, browsing experience satisfaction will be highest in the Ad-blocking condition and lowest in the Targeted Ads condition (Ad-blocking > Anti-tracking > Targeted Ads).*

Theoretical Logic 2: The Intrusiveness and Reactance Engine

This perspective argues that the negative psychological costs associated with the modern advertising ecosystem, particularly the tracking component, overwhelm any potential benefits in product matching or discovery. The core mechanism is psychological reactance (Rosenberg and Siegel 2018). The awareness of being constantly monitored, having one's data collected and analyzed, and being targeted based on that surveillance can evoke strong negative affective states. Consumers report feeling that their privacy has been invaded and find the practice of behavioral tracking "creepy" (Moore et al. 2015). This sense of intrusion can trigger psychological reactance, a motivational state aimed at restoring a threatened sense of freedom and control (Brehm and Brehm 2013; Yeo et al. 2025). These negative feelings are likely to contaminate not only the browsing experience itself but also the evaluation of any products encountered or purchased within that environment. Therefore, this logic predicts a straightforward relationship: the less intrusive the environment, the higher the overall satisfaction. The Ad-blocking condition, being the most private and least intrusive, should yield the highest satisfaction, while the Targeted Ads condition, being the most intrusive, should yield the lowest.

Hypothesis 2b*: *Both purchase satisfaction and browsing experience satisfaction will be highest in the Ad-blocking condition, significantly lower in the Anti-tracking condition, and lowest in the Targeted Ads condition (Ad-blocking > Anti-tracking > Targeted Ads).

Theoretical Logic 3: The Affective Wash-Out Engine

This final view proposes that the various positive and negative affective components of the advertising experience may effectively cancel each other out, leading to no net difference in overall satisfaction across conditions. This "wash-out" effect can be conceptualized in several ways. For instance, in the Targeted Ads condition, the positive feeling from finding a well-matched product via a behaviorally targeted ad might be nullified by the negative "creepy" feeling of being tracked that accompanied the discovery. Conversely, in the Ad-blocking condition, the positive feeling of a clean, non-intrusive browsing experience might be offset by the negative feeling of a more frustrating or lengthy search process required to find a suitable product. This logic suggests that consumers' net affective state remains relatively constant across these different trade-offs.

The lab experiment by Frik et al. (2020) provides the most direct evidence for this perspective, as they found no significant differences in participants' satisfaction with the products they chose, the prices they paid, or the perceived quality of those products between their ad-blocking and no-blocking conditions. Other research has also found null effects of personalization on satisfaction in various contexts, with some studies showing that the direct effect of personalization on perceived intrusiveness is not significant, possibly because the value offered by personalized ads makes them less likely to be perceived as unwanted (for a meta analysis, see Yeo et al. 2025).

Hypothesis 2c: *There will be no significant difference in purchase satisfaction or browsing experience satisfaction across the three experimental conditions (Targeted Ads = Anti-tracking = Ad-blocking).*

Summary of Competing Hypotheses

The following table summarizes the competing hypotheses and the predicted pattern of results across the key outcome variables.

TABLE 1

SUMMARY OF COMPETING HYPOTHESES AND PREDICTED PATTERNS OF RESULTS

Outcome Variable	**Theoretical Logic 1 (Informative Engine)**	**Theoretical Logic 2 (Market-Shuffling and User Experience Engine)**	**Theoretical Logic 3 (Peripheral Influence Engine)**
Total Purchase Expenditure	Targeted Ads > Anti-tracking > Ad-blocking	Ad-blocking > Targeted Ads ≈ Anti-tracking	Targeted Ads = Anti-tracking = Ad-blocking
Purchase Frequency	Targeted Ads > Anti-tracking > Ad-blocking	Ad-blocking > Targeted Ads ≈ Anti-tracking	Targeted Ads = Anti-tracking = Ad-blocking
Outcome Variable	**Theoretical Logic 1 (The Precision-Friction Engine)**	**Theoretical Logic 2 (The Intrusiveness**	**Theoretical Logic 3 (The Affective Wash-Out Engine)**

		and Reactance Engine)	
Browsing Satisfaction	Ad-blocking > Anti-tracking > Targeted Ads	Ad-blocking > Anti-tracking > Targeted Ads	Targeted Ads = Anti-tracking = Ad-blocking
Purchase Satisfaction	Targeted Ads > Anti-tracking > Ad-blocking	Ad-blocking > Anti-tracking > Targeted Ads	Targeted Ads = Anti-tracking = Ad-blocking

5. EXPERIMENTAL DESIGN

This section details the pre-specified methodology for the field experiment, designed to provide a test of the competing hypotheses. The study protocol has been approved by the Institutional Review Board (IRB) of the lead institution. The infrastructure has been iteratively developed and tested (see Appendix C of the companion document), and has been recently deployed. The recruitment and data collection are in process, with an expected completion by 2026. Given the experiment's longitudinal design, the complexity of the infrastructure, and the vastness of the data fields collected by it, data collection is continuously monitored to verify successful implementation. However, the hypotheses presented in this Registered Report—concerning consumer purchases, associated outcomes, and satisfaction—have not yet been tested, preserving the integrity of this Stage 1 registration. Additional details are available in the draft preregistration document included in this Registered Report submission.

Design

The study employs a three-group (Condition: Targeted Ads, Anti-tracking, and Ad-blocking) between-subjects longitudinal design.

Participants and Recruitment

The target sample size is 1,200 participants, with 400 participants randomly assigned to each of the three experimental conditions. This sample size was determined based on power analyses aiming to detect small-to-medium effect sizes. The power calculations that led to selecting this sample are discussed in Appendix D of the companion document.

Participants are recruited from the United States through a combination of channels, including online ads, established online research panels, and university-affiliated participant pools. Participants are compensated for their time and for the data they provide, with payment installments: they receive a $15 initial payment upon onboarding; $5 monthly payments after completing the first and the second monthly surveys; and a payment of $20 after completing the third (and final) monthly survey. In addition, participants who complete the study are included in a lottery that pays $200 to one out of every 100 participants.

Eligibility is determined based on pre-set criteria. Participants must be 18 years or older and be U.S. residents; they must use their own computer (not a shared or a corporate device) with Windows operating system and the Google Chrome browser as their primary means of accessing the internet for personal browsing and shopping; they must have completed at least one online purchase in the last month; and they must not be current users of ad-blocking or anti-tracking software.[5] The exclusion of current users of such tools is necessary to ensure a clean causal estimate from the randomized assignment, by ensuring the experimental treatment is the same across participants in each condition. Future iterations of this experiment can relax this criteria, as the infrastructure is capable of handling both users and non-users of those tools.

[5] Participants also cannot use Proton or Zoho as their principal email accounts, because of incompatibility with our infrastructure. On mobile, participants must be Chrome Android users or Safari/Chrome iOS users.

Procedure

The participant's journey proceeds through the following stages over a period of three months:

Recruitment and Screening Survey.

Potential participants are directed to an online screening survey on Qualtrics to determine eligibility based on the criteria listed above. Those who pass the screening survey are immediately invited to visit a URL to learn more about and enroll in the study.

Onboarding: Informed Consent, Entry Survey, Software Installation and Randomization.

Eligible participants who click on the URL link are directed to an overview of the study's purpose and procedures. They are informed that the study requires the installation of custom research software on their primary computer and mobile device, that this software monitors their online browsing and shopping-related emails, and that the software may include ad-blocking or anti-tracking features depending on their random condition assignment. They are then quizzed about their understanding of the study procedures. Once they pass the quiz, informed consent is obtained electronically. The Entry Survey collects baseline data, including demographics, information about their mobile devices, prior use of ad-blocking or anti-tracking tools, baseline online shopping frequency and preferences, and attitudes toward advertising and privacy. Random assignment to the three conditions occurs during the Entry Survey and is blind to the participant. The survey is administered before any randomized experimental treatments, such as ad-blocking or anti-tracking, are activated. Participants are also guided through the installation of the desktop study software, which exerts and activates the experimental conditions. In addition, they are asked to adjust the settings and/or install software on their mobile devices to match the experimental conditions they are assigned to. The experimental infrastructure includes verification and compliance checks to ensure that participants follow the assigned installation and configuration instructions. The onboarding flow and Entry Survey are identical across participants.

Participants who follow all required instructions are enrolled into the study, completing the onboarding phase.

Longitudinal Data Collection. The experimental period for enrolled participants lasts three months. During this time, the software passively collects data on participants' browsing behavior, ad exposure, online purchases, and more. The three-month duration is chosen to be long enough to capture the cumulative effects of advertising (or its absence) and to record a sufficient number of purchase instances for analysis.

Monthly Surveys. At the end of month 1 and month 2, participants are prompted to complete a short online survey. These surveys include some of the measures also collected during the Entry Survey.

Exit Survey. At the conclusion of the three-month period, participants complete an Exit Survey. This survey collects again some of the measures also collected during the entry and monthly surveys, including overall evaluations of their browsing and shopping experiences during the duration of the experiment. Participants are then provided with instructions for uninstalling the study software.

Experimental Manipulations

The core of the experiment lies in the differential functionalities of the study software across the three conditions, which have been discussed in Section 3.

Measures

The variables we use to test the experimental hypotheses are operationalized as follows, distinguishing between data collected passively by the software and data collected via surveys using questions and scale derived from the literature.

Purchase Behavior (Observed Data):

Total Online Expenditure: The sum of the amount paid (in USD) for all detected online purchases, extracted from parsing (and de-duplicating) purchase confirmation URLs/HTMLs, complete historical Amazon purchase records, mobile purchase confirmation URLs, and purchase confirmation emails. We use multiple sources to maximize coverage of purchases across channels and devices.

Purchase Frequency: The total count of distinct online purchase events detected during the study period.

Average Price Paid (as an exploratory measure, as we do not have a pre-existing hypothesis): The mean price per item purchased, calculated as total expenditure divided by the total number of items purchased.

Satisfaction (Survey Data):

Purchase Satisfaction: measured across the Entry, Monthly, and Exit surveys. Participants are asked to rate their satisfaction on 5-point Likert scales (e.g., “Over the last four weeks, I was satisfied with the products/services I purchased online”; “Over the last four weeks, I was satisfied with the prices I paid for the products/services I purchased online”; etc)

Browsing Experience Satisfaction: measured across the Entry, Monthly, and Exit surveys using 5-point Likert scales (e.g., “Over the last four weeks, how would you rate your overall browsing experience?”; “Over the last four weeks, when visiting non-shopping websites, how satisfied or dissatisfied were you with the selection of online content?”; etc).

Covariates and Moderators (Entry Survey Data): Variables collected in the Entry Survey are used as control variables in robustness and, for baseline privacy attitudes, in planned moderation analyses. These include: demographic characteristics (age, gender, income, education), prior use of ad-blocking software, baseline online shopping frequency, and baseline privacy attitudes (measured using established scales, e.g., from Turow, Hennessy, and Draper 2015).

6. DATA ANALYSIS PLAN

This section summarizes the pre-specified analytical pipeline, from data preparation to hypothesis testing.

Data Preparation and Exclusion Criteria

Prospective participants who appear to be bots or fraudulent respondents are removed during the enrollment phase based on signals captured by the study software unrelated to the assigned condition: IP addresses, device fingerprints, duplicate-respondent checks, and unusually low browsing or email activity (see details in the draft preregistration document). Because these checks are applied identically across conditions and are blind to assignment, they function as screening rather than post-randomization exclusion. The number of removals at each stage, by condition, will be reported.

Raw data from the software logs and surveys for participants who complete onboarding and are enrolled into the study will be processed and cleaned. We define two analysis samples. The primary sample, used for the modified intention-to-treat (mITT) analysis, comprises all randomized participants who pass onboarding and contribute at least one full month of instrumented data. The mITT will be our primary analysis, and no participants who complete onboarding will be excluded from this sample for post-randomization noncompliance or attrition. The completer-only sample, used in robustness analyses, comprises participants who complete all three months in the study (see additional details in the draft preregistration document).

Outlier Handling

Because online expenditure is right-skewed and a small number of participants may make unusually large one-off purchases, the primary specification analyzes total expenditure trimmed at the top 2% of the distribution. The trimming threshold is computed on the pooled sample across conditions, so the same cutoff applies to all conditions. Such extreme purchases are driven largely by idiosyncratic factors, are unlikely to be responsive to the experimental manipulations, and inflate variance in ways that can mask treatment effects on typical spending; the primary estimand therefore targets the effect on typical online expenditure. The number of trimmed observations per condition will be reported. Untrimmed expenditure in levels and log-transformed expenditure will be reported as robustness checks.

Manipulation and Compliance Checks

Technical Check.

Prior to launch, all study software was repeatedly tested to confirm that experimental conditions functioned as intended and cannot be altered by the user. During the study, automated scripts continuously assess the integrity of the experimental manipulations. The scripts continuously analyze incoming data to verify that each participant's assigned experimental condition is correctly implemented and reported by the participant's device. On the computer, manipulation fidelity is verified by examining captured advertisements, rendered browsing HTML, and related page-level artifacts, ensuring confirmation that ads are shown or suppressed as intended and ensuring the correct operation of tracking and anti-tracking mechanisms. These automated checks are supplemented by regular human spot checking of live data to identify anomalies, inconsistencies, or failures that may not be detectable algorithmically. Together, these sources provide multiple, converging pieces of evidence that the experimental manipulations are active and operating as designed throughout the study period. Additional details about past pilots and tests as well as recurrent technical checks and verifications of the infrastructure's ability to capture complete and accurate data and correctly exert the intended experimental conditions are presented in Appendix C of the companion document.

When reporting the experimental results, we will also present the results of manipulation checks, including measures such as recorded advertising volume and tracking/cookie footprint.

Hypothesis Testing: Primary Analyses

We first estimate a modified intention-to-treat (mITT) effect on the three-month participant-level aggregate. This primary analysis includes all randomized participants who pass onboarding and contribute at least one full month of instrumented data (primary sample). Aggregates for participants with partial observation are scaled to the full window relative to their observed participation period. We then compute a robustness analysis for the completer-only sample following the exclusion criteria explained above, and a monthly-panel specification as robustness checks.

Rather than relying on a simple omnibus F-test of the Condition variable, we will test our competing hypotheses using a set of two pre-planned orthogonal contrasts. This approach provides a more direct and powerful test of our specific theoretical questions.

Contrast 1 (Ad Presence Effect): This contrast will compare the average of the two ad-exposed conditions to the ad-blocking condition: ("Targeted Ads"+"Anti-tracking")/2−"Ad-blocking". This tests the overall effect of being exposed to advertising versus not.

Contrast 2 (Targeting Effect): This contrast will compare the two ad-exposed conditions directly: "Targeted Ads" – "Anti-tracking". This estimates the incremental causal effect of behavioral tracking and targeting, holding the presence of advertising constant.

Interpretation of Null Results: Hypotheses 1c and 2c predict no differences across conditions. However, we will not treat non-significance alone as support for them. For any primary outcome not statistically distinguishable from zero, we will report equivalence tests (TOST) and the smallest equivalence bound containing the 90% confidence interval, characterizing such results as bounding plausible effect sizes rather than demonstrating the absence of an effect. The full procedure is pre-specified in the draft preregistration document and Appendix D of the companion document.

Pre-specified regression equation

The primary specification analyzes the treatment effects of the entire experimental period and will be estimated as follows for each contrast.

Contrast 1: $Y_i = \beta_0 + \beta_1 \mathrm{AdPresence}_i + \gamma' X_i + \epsilon_i$

Where Y_i corresponds to the value of the dependent variable's aggregate outcomes over the three-month study period. $\mathrm{AdPresence}_i$ corresponds to the contrast coefficients which in this case takes the values (0.5, 0.5, -1) for participants in the Targeted Ads, Anti-Tracking, and AdBlocking conditions respectively. X_i is a vector of baseline covariates (included in secondary specifications only, primary specification is unadjusted). ϵ_i is the residual. The coefficient β_1 is the primary estimand of interest and represents the difference in mean outcome between the average of the two ad-exposed conditions and the ad-blocking condition.

Contrast 2: $Y_i = \beta_0 + \beta_2 \mathrm{TargetingEffect}_i + \gamma' X_i + \epsilon_i$

The specification for contrast 2 is analogous, with the difference that the contrast coefficients take the values of (1, -1, 0) for participants in the Targeted Ads, Anti-Tracking, and AdBlocking conditions respectively. The coefficient β_2 is the primary estimand and represents the difference in mean outcome between the Targeted Ads condition and the Anti-tracking condition, estimating the incremental effect of behavioral tracking and targeting while holding the presence of advertising constant.

For binary outcomes (e.g., purchase incidence over the study period), we will estimate linear probability models as our primary specification and logit models as a robustness check. Linear probability models yield coefficients that are straightforward to interpret as changes in probabilities and are flexible with respect to the inclusion of rich sets of control variables, while logit models respect the bounded nature of the outcome. We will report logit results as average marginal effects to facilitate direct comparison with the LPM estimates. For continuous dependent variables (e.g., total expenditure over the study period), we will estimate ordinary least squares regressions on the participant-level aggregate. The primary specification includes the contrast-coded predictors with heteroskedasticity-robust standard errors. We additionally report specifications that add the pre-specified baseline covariates as robustness checks.

Supplementary Analysis: Monthly Panel with Participant Random Intercepts

In addition to the primary three-month aggregate analysis, we will conduct a supplementary analysis using monthly purchase data, treating the data as a panel with three time periods per participant. The potential advantage of this specification is that it allows us to model stable participant-level heterogeneity through a participant-specific random intercept, which captures time-invariant characteristics—baseline spending propensity, income, demographics, and other stable attributes—that contribute to residual variance. Its main advantage arises under attrition: when some participants do not complete all three months, the likelihood-based mixed model uses all available person-months and remains consistent as long as dropout is unrelated to a participant's purchasing outcomes once assigned condition and baseline characteristics are accounted for. This assumption is less restrictive than that required for the complete-case aggregate analysis, which yields unbiased estimates only when dropout is entirely unrelated to participants' characteristics. We use mixed-effects models rather than participant fixed effects because each participant is assigned to a single condition, making the treatment indicator time-invariant within participants; participant fixed effects would absorb it and preclude identification of the contrasts.

The specification follows the same logic as the primary analysis, but adding month fixed effects, and random intercept. Specifically:

Contrast 1: $Y_{i,t} = \beta_0 + \beta_1 \text{AdPresence}_i + \alpha_t + \gamma' X_i + u_i + \epsilon_{i,t}$

Contrast 2: $Y_{i,t} = \beta_0 + \beta_2 \text{TargetingEffect}_i + \alpha_t + \gamma' X_i + u_i + \epsilon_{i,t}$

Where $Y_{i,t}$ is the participant's outcome in months $t \in \{1, 2, 3\}$, *AdPresence* and *TargetingEffect* correspond to the contrast-coded variables defined above, α_t are month fixed effects, X_i is a vector of baseline covariates, and $u_i \sim N(0, \sigma_u^2)$ is a participant-level random intercept capturing unobserved participant heterogeneity. Finally, $\epsilon_{i,t} \sim N(0, \sigma_\epsilon^2)$ is the residual. The model will be estimated as a linear mixed-effects model.

Missing Data and Attrition

The primary analysis follows an intention-to-treat framework using all available outcome data. We will report retention rates by condition and compare baseline characteristics of retained and attrited participants. If overall attrition exceeds 10%, and rates differ across conditions, we will implement inverse-probability weighting as a pre-specified sensitivity analysis: retention will be modeled as a function of assigned condition and the pre-specified baseline covariates using logistic regression, and the primary specifications re-estimated with participants weighted by the inverse of their predicted probability of retention.

7. GENERAL DISCUSSION

This Registered Report proposes a large-scale field experiment to provide a causal analysis of an open question: what is the effect of the modern online advertising ecosystem (and, conversely, of privacy tools that curtail it) on consumer purchases and satisfaction? Traditional advertising theories predate the age of pervasive, data-driven personalization, and existing empirical evidence is fragmented because of methodological hurdles. By varying advertising and tracking across the broader digital ecosystem and linking these conditions to search, purchasing, and satisfaction, this Registered Report provides a test of how advertising shapes contemporary consumer behavior. By pre-registering competing macro-theories of the role of advertising in consumer behavior and a rigorous analysis plan, the study is designed to vet which of the canonical roles of advertising is most salient in the modern advertising ecosystem, independent of the direction of the results.

If our results support the **Informative Engine** (Hypothesis 1a), it would provide evidence for the industry's long-held claims about the value of advertising and targeting. This would imply that privacy regulations that limit tracking, such as GDPR and ATT, may come at a cost not only to firms but also to consumer purchases and satisfaction. Such a finding would have implications for policymakers, by suggesting a trade-off between consumer privacy protections and the intensity of online purchasing behavior.

Support for the corresponding **Precision-Friction Engine** (Hypothesis 2a) would add an important dimension to this finding. If the results showed that purchase satisfaction is highest in the Targeted Ads condition, while browsing satisfaction is highest in the Ad-blocking condition, it would suggest that the economic effects of online advertising are linked to satisfaction through better-matched products and higher utility while simultaneously introducing an online experience cost. This finding would reconcile the seemingly opposing claims of a "win-win" proposed by the industry with the reported constant concerns and dissatisfaction with online advertising. It would suggest a fundamental trade-off: the very mechanism that drives economic activity and satisfaction with products simultaneously degrades the overall experience of being online, creating a persistent friction in the digital environment.

Conversely, if the results support the **Market-Shuffling and User Experience Engine** (Hypothesis 1b), this would imply that the negative experiential costs of advertising—annoyance, distraction, and privacy intrusion—may outweigh its informative benefits. In this case, privacy-enhancing regulations and technologies could increase online purchasing activity by reducing browsing frictions and improving the user satisfaction. Such findings would suggest that the structure of digital markets is shaped not only by the informational role of advertising but also by its experiential consequences.

This conclusion would be reinforced if the results also support the **Intrusiveness and Reactance Engine** theory of satisfaction (Hypothesis 2b). A finding that purchase and browsing satisfaction are highest in the Ad-blocking condition and lowest in the Targeted Ads condition would suggest that the negative psychological costs of targeted advertising—such as feelings of being monitored and the "creepiness" of surveillance—overwhelm any benefits of personalization. In this scenario, the increase in purchasing is driven by a holistically better and less intrusive experience. It would indicate that environments with fewer ads and less tracking are associated with higher levels of purchasing and reported satisfaction, informing ongoing debates about privacy-enhancing policies and technologies.

Finally, results consistent with the **Peripheral Influence Engine** (Hypothesis 1c)—treatment effects statistically indistinguishable from zero, with the equivalence procedure bounding plausible effects below meaningful magnitudes—would suggest that the aggregate impact of display advertising on consumer purchasing is more limited than commonly assumed. In this scenario, display advertising may exert modest influence over most purchasing decisions, with effects that primarily reflect shifts across firms rather than substantial changes in overall purchasing levels or reported satisfaction. This would align with recent large-scale experimental findings from single-platform studies (such as Brynjolfsson et al. 2025) and meta-analyses (Korkames, Stanley, and Stremersch 2025) that find very small aggregated effects of advertising, challenging decades of marketing assumptions and suggesting that the intense policy debates over tracking and targeting may be focused on a less impactful mechanism than is commonly believed.

A null effect on purchasing, if accompanied by tight equivalence bounds, would be consistent with the **Affective Wash-Out Engine** for satisfaction (Hypothesis 2c), which also predicts no significant difference across conditions. Such a result would suggest that the various positive and negative aspects of the advertising experience—the utility of a helpful ad versus the disutility of annoyance and "creepiness"—effectively cancel each other out, leading to no net change in either spending or satisfaction. This would align with prior lab experiments that found no effect of ad-blocking on satisfaction (Frik et al. 2020) and would suggest that, for the average consumer, the aggregate behavioral and experiential effects of advertising may be limited. In this scenario, advertising's primary economic effect may operate through shifts in purchasing across firms, rather than through substantial changes in overall purchasing levels or reported satisfaction. Accordingly, each possible pattern of results has distinct theoretical and policy implications.

Limitations of the Infrastructure and the Study Design

While the proposed field experiment offers advantages in terms of causal inference and ad ecosystem-wide focus, it is important to acknowledge its inherent limitations. First, the study's technical requirements—specifically, the use of the Google Chrome browser on a Windows operating system—limit the generalizability of the findings to users of other browsers (e.g., Safari, Firefox) and operating systems (e.g., macOS, Linux), as behaviors may differ across platforms. That noted, Chrome on Windows represents a large segment of internet users (StatCounter 2025; W3Counter 2025), and random assignment preserves internal validity of treatment comparisons within the recruited sample. Second, the three-month duration of the experiment, while sufficient to capture many purchasing cycles and short-term behavioral changes, may not be long enough to observe the full extent of long-term effects. Consumer habits, brand loyalties, and adaptation to a new advertising environment may evolve over a longer period. Third, while our infrastructure is designed to capture a comprehensive view of online behavior, it cannot achieve omniscience. We cannot track purchases made entirely offline without any online component, nor can we perfectly track behavior across all of a participant's devices, particularly when participants use additional unenrolled devices or when installation and continued compliance vary over time. Furthermore, participants will still be exposed to advertising through other channels not monitored by our software, such as television, radio, and print media, which represents an unobserved source of influence on their behavior. Fourth, there are limitations regarding representativeness of our sample: we are only recruiting participants who are not currently using ad-blocking or anti-tracking technology—which is representative of the current majority of Internet users, but not all users. This limitation is necessary to ensure clear segmentation of our conditions, as current use of such privacy measures may otherwise affect participants' browsing expectations. Importantly, relative to platform-specific field experiments conducted within individual 'walled gardens,' the present design can realistically achieve only a much smaller sample size, but can capture behavior across websites and platforms, thus allowing ecosystem-wide manipulation of tracking and advertising exposure and enhancing ecological scope. Relatedly, this study suffers from a limitation common to other studies that rely on installing tracking software on participants' devices: participation in the study requires installation of research software that collects granular browsing and transaction-level data, including page-level metadata and purchase confirmation emails, and participants who hold strong privacy concerns may not self-select to participate in a study that observes their online behavior; or may not be convinced to participate for the compensation amount we offer. While such comprehensive instrumentation may limit participation among highly privacy-sensitive individuals, random assignment preserves internal validity of treatment comparisons within the recruited sample. Opt-in digital behavior panels using comparable instrumentation are common in the study of online markets (e.g., Comscore, Webmunk). As we capture at entry baseline measures of privacy attitudes and other attitudes towards tracking, targeting, and online ads, we will examine whether treatment effects vary along these dimensions, as well as how our baseline measures (including demographics, browsing trends, and privacy attitudes) differ from those calculated for representative samples of the US online population.

Finally, as with any study involving the monitoring of behavior, the Hawthorne effect is a potential concern. Participants' awareness that their online activities are being recorded could lead them to alter their natural browsing and purchasing behaviors, potentially biasing the results. While random assignment ensures this bias would be evenly distributed across conditions, and while the longitudinal nature of the study (three months) can dissipate the impact of such an effect, it remains a limitation on the absolute interpretation of behaviors.

Future Directions

The rich dataset generated by this experiment can open several avenues for future research, regardless of which primary hypotheses are supported. A key direction will be to explore heterogeneous treatment effects in greater detail. While we pre-specify moderation analyses based on baseline privacy attitudes, future exploratory work could examine how effects differ across a wider range of demographic variables (e.g., age, income), psychological traits, and product categories. Understanding for whom and for which types of purchases advertising has the largest impact is a critical question for both theory and practice.

Another avenue involves a deeper investigation of the psychological mechanisms underlying the observed effects. While our primary outcomes are behavioral, the survey data on satisfaction provides a window into subjective experiences. Future studies could build on these findings with more targeted experiments or surveys designed to explicitly measure constructs like psychological reactance, cognitive load, annoyance, and perceived value from advertising.

Finally, the findings from this study will provide a strong foundation for future research on the evolving advertising landscape. As new technologies (e.g., AI-driven creative, privacy-preserving measurement) and regulations emerge, the baseline effects established in this experiment will be invaluable for contextualizing the impact of these changes. Future experiments could replicate this design in different cultural contexts, on different platforms (e.g., focusing exclusively on mobile), or over longer time horizons to build a more complete and dynamic understanding of the role of advertising in consumer life.

8. CONCLUSION

The role of online advertising and privacy technologies in the digital economy is a subject of intense debate, yet it rests on a fragile empirical foundation when it comes to its impact on consumers. Industry proponents, privacy advocates, and academic researchers have advanced plausible but contrasting theories about whether the current ecosystem helps, harms, or is simply irrelevant to consumer purchases and satisfaction. By employing a novel three-condition, longitudinal field experiment, we create randomized contrasts that allow us to estimate the effects of advertising exposure separately from the incremental effects of behavioral targeting. This methodological approach, combined with the scale and duration of the data collection, can allow for a rigorous test of the competing theoretical frameworks that currently define the debate. The pre-registration of our hypotheses and analysis plan ensures that the study's contribution will be judged on the importance of its questions and the soundness of its methods. Ultimately, this research aims to provide a new assessment of how the complex advertising ecosystem affects consumers' purchasing decisions and online experiences.

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