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ORIGINAL EMPIRICAL RESEARCH

Native advertising effectiveness: The role of congruence and consumer annoyance on clicks, bounces, and visits

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Abstract

In response to increased avoidance of traditional banner advertising, publishers have turned to a subtler form of display advertising called native advertising. Unlike traditional banner ads, native ads are intentionally designed to be cohesive with editorial content and assimilated into the design of the publisher's website. We examine the performance of native advertising placements across three studies. In Study 1, we use a large dataset from a native advertising platform to examine the interplay of ad placement and ad content. We find that clicks are higher when ads are (1) delivered in-feed and (2) contain lower levels of selling intent, highlighting the interplay between the ad content and delivery. Study 2 confirms that in-feed placements experience higher clicks, but they also result in more bounces relative to in-ad placements. As a result, their effect on net visits is similar to in-ad placements at a higher cost. To further understand this phenomenon, we conducted a lab study (Study 3), which shows that when consumers are redirected to an advertiser's site from an in-feed (versus in-ad) placement they experience higher annoyance and, ultimately, higher bounce intentions and reduced advertiser purchase intentions.

Keywords Native advertising · Digital marketing · Digital advertising · Advertising

As media consumption has shifted to digital, investments in online display advertising have risen steadily with spending in the United States expected to exceed $140 billion in 2022 (eMarketer, 2022). However, with consumers becoming increasingly savvy at avoiding banner ads (Chatterjee, 2008; Cho & Cheon, 2004), advertisers are constantly looking for more effective methods for their digital campaigns. In the display advertising space, one proposed solution is native advertising. Unlike traditional display ads, native ads are designed to blend in with the publisher's content by utilizing similar fonts, colors, and other features of the publisher's website (Wojdynski & Evans, 2016). As a result, consumers view the content similarly to editorial content and are more likely to click on them than banner ads (Aribarg & Schwartz, 2020).

With click-through rates declining for traditional display ad formats, the promise of more effective display ads has captivated advertisers. From 2020 to 2021, the number of brands using native advertising more than doubled (Statista, 2022) and spending has increased 426% since 2016 (eMarketer, 2022). While advertisers have been quick to adopt this new advertising format, there are questions as to whether native ads are truly more effective or simply confusing consumers. Recent research on native display ads suggests that native ads, particularly those delivered in-feed, are more likely to be clicked on because consumers confuse ad content with editorial content (Aribarg & Schwartz, 2020). Although more clicks would seem appealing to advertisers, display ads are typically bid—and paid for—on a per click basis. As a result, total clicks are perceived as more of a

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publisher-focused metric (Wang et al., 2019). Depending upon their campaign's goal (i.e., drive traffic, stimulate a sale, encourage a subscription), advertisers should be concerned with consumer responses after the click.

With respect to post-click assessments, research suggests that consumers may feel annoyed upon realizing the content they are trying to consume is indeed advertising (Wojdynski, 2016). Accordingly, the FTC has established—and enforces—guidelines surrounding the disclosure of native display ads (Federal Trade Commission, 2015). While properly disclosed native display ads help consumers understand that they are reading advertising content, research finds that consumers still perceive the ad as similar to editorial content (Aribarg & Schwartz, 2020). Compared to a non-native ad, it is theorized that once consumers are redirected to the advertiser's landing page, they will become relatively more annoyed and have lower conversion rates (Wang et al., 2019). Curiously, little research has addressed this phenomenon and assessed how consumers react after clicking on native ads.

To address competing perspectives and contribute to this growing literature base, our research aims to provide fresh insight into how two key structural elements of native display ads—ad content and ad placement—influence consumer response to these ads. We begin our research with an analysis of over 250,000 native advertising campaign scenarios to explore how decisions related to the placement and content of native display ads influence click-throughs (Study 1). While driving clicks is an important goal, advertisers are just as— if not more—concerned with converting these clicks into quality leads. This begins with ensuring that consumers have a positive experience with the landing page. To address this, we conduct a field experiment to examine how native ad placement and message-related factors influence a consumer's decision to bounce from the landing page (Study 2). We then conduct a lab study to further understand and measure the mechanisms underlying our theorizing (Study 3). Taken together, our studies can provide a broader perspective on native advertisements are processed by consumers.

Our research contributes to the marketing literature and practitioner knowledge in several ways. First, research on native advertising suggests that consumers may be annoyed following a click on a native ad (Wang et al., 2019; Wojdynski, 2016). Our research provides unique insight by showing that user annoyance is initiated immediately after being redirected to the advertiser's website. From a practitioner perspective, this has important implications for bidding. In finding that consumers are more likely to bounce from in-feed placements, a cost-per click (CPC) model would appear to be a suboptimal bidding scheme for the advertiser. As the advertiser pays the publisher for every click, regardless of whether they bounce, any bounce from the landing page is going to negatively affect the return on investment of the advertising campaign.

This research also builds upon prior calls in the literature to assess the influence of message content on native advertising effectiveness (e.g., Harms et al., 2017). While traditional display advertising often uses explicitly promotional appeals that are high in selling intent to garner attention, advertisers have recently started to explore content marketing strategies that feature appeals low in selling intent. Often these low selling intent ads appear unbranded and are positioned as supplemental editorial content to drive clicks from consumers interested in the advertised information. Notably, while Aribarg and Schwartz (2020) show that such ads can achieve high click-through rates, they do not explore how ad content's inherent promotional nature interacts with its placement. Our study sheds light on this area by exploring the interaction between message selling intent and ad placement, we extend prior research by more fully accounting for both the design (high versus low selling intent) and deployment (placement) of native ads and their landing pages, thus providing a better baseline of their ability to drive value for brands.

Finally, our second study allows for a head-to-head assessment of in-ad versus in-feed placements with respect to clicks, bounces, and visits. We find that in-feed ads experience both higher clicks and higher bounces compared to in-ad placements. These effects are offsetting to the extent that net visits generated via in-ad and in-feed placements are similar despite the higher cost per visit for in-feed placements. This nuanced series of effects shine a light on opportunities to more effectively deploy native ads using cost per thousand impressions (CPM) bidding schemes rather than cost per click (CPC) bidding strategies where in-feed ads underperform.

Relevant literature and hypothesis development

Native advertising

As a new form of digital advertising, there are different definitions and viewpoints concerning native advertising. One point of consistent agreement is the notion that native advertisements are explicitly designed to match "the form and appearance of editorial content from the publisher" (Wojdynski & Evans, 2016, p. 157). Given this broad criterion of matching the form and appearance of a publishing website, native advertising is primarily delivered in one of three formats: (1) sponsored content, (2) sponsored social media posts, and (3) sponsored hyperlink listings (Wojdynski, 2016). Similar to advertorials in physical magazines, sponsored content is advertising content that is hosted on a publisher's website, leveraging the existing fonts, colors, and page design (Wojdynski & Evans, 2016). An example

Table 1 Overview of research on native advertising

Context/Study	Types of Studies	Ad Types	Contingency Factors		Outcome Type	
			Advertiser-Controlled	Publisher-Controlled	Pre-Click	Post-Click
Display Ads						
Current Paper	Secondary Data; Field Experiment; Lab Experiment	Native in-feed; Native in-ad	Selling Intent	Internal v. External Re-Direct	Behavioral (Clicks)	Behavioral (Bounces and Net Visits) Attitudinal (Future Purchase Intentions)
Aribarg & Schwartz 2020	Lab; Field Experiment	Native in-feed; Banner ad		Disclosure Prominence	Behavioral (Click); Attitudinal	
Kim et al., 2019a	Lab	Native in-ad; Banner ad	Content Nativeness		Attitudinal	
Kim et al., 2019b	Lab	Native in-ad; Banner ad	Number of Ad Placements		Attitudinal	
Wang et al., 2019	Secondary Data	Native in-feed	Audience Gender; Audience Age	Rank Position	Behavioral (CTR)	Behavioral (Conversion Rate)
Social Media Ads						
Boerman et al., 2017	Lab	Native in-feed	Authorship	Disclosure Presence	Attitudinal	
Hayes et al., 2020	Lab	Native in-feed	Authorship; Ad-Message Relevance	Disclosure Presence	Attitudinal	
Jung & Heo 2019	Lab	Native in-feed		Disclosure Prominence	Attitudinal	
Kim et al., 2019b	Lab	Native in-feed	Source Type; Appeal Type		Attitudinal	
Search Ads						
Sahni & Nair, 2020	Field Experiment	Native in-feed		Disclosure Prominence	Behavioral (CTR)	Behavioral (Conversion Rate)

of this in practice is Forbes BrandVoice, where brands can purchase long-form advertising space on Forbes website.

Native advertising also encompasses a variety of short-form digital advertising formats. Major social media outlets like Facebook and X offer native ads on their platforms where the sponsored posts match the look and feel of the user's social feed (Boerman et al., 2017; Hayes et al., 2020). Finally, there are sponsored hyperlink listings, which can come in the form of display ads or search ads. While search engines such as Google have seamlessly integrated ads into organic listings for many years (e.g., Sahni & Nair, 2020), perhaps the most dramatic change has come in display advertising on digital publishing platforms (i.e., news websites, blogs, etc.). This is largely because traditional display advertising formats are delivered in specific areas of the webpage (e.g., header, side) that are intentionally delivered away from editorial content. However, with native ads, they are served within and alongside the editorial content in a manner designed to have them blend in with traditional news content.

Given the rapid shift in how firms are deploying native display ads, we seek to build on the base of early research on native advertising to examine the effectiveness of native ad placements. As indicated in Table 1, most of the literature on native display ads centers around publisher-controlled factors, such as disclosures (e.g., Aribarg & Schwartz, 2020) and serial rank position (Wang et al., 2019). The limited research that does touch on advertiser-controlled factors focuses on targeting decisions, such as contextual relevance (e.g., Kim et al., 2019a; Hayes et al., 2020) and demographic targeting (Wang et al., 2019). Others have explored the role of message content under the broader umbrella of native advertising, such as sponsored articles (e.g., Saenger & Song, 2019) and social media endorsers (Kim, Song & Yang, 2021). Although these findings provide useful guidance for our conceptual development, none of the existing research has considered how ad content and ad placement *jointly* influence native display advertising effectiveness. Consequently, this research seeks to provide a comprehensive assessment of how marketers should approach native display advertising.

Changes in native advertising performance across placements

In the evolving landscape of digital advertising, the placement and presentation of ads play a pivotal role in consumer engagement. Recent trends indicate a shift towards more disguised forms of display advertising, where publishers now offer advertisers the ability to add native elements to display ads. This not only includes design elements such as publisher fonts and color schemes, but also where the content is placed. Traditionally, publishers have reserved space for display ads that are distinct from editorial content—typically on the right or top of the web page. Consistent with the IAB (2013), we refer to placements in traditional ad space as in-ad placements. However, publishers have started to offer native ad placements directly in their editorial feed (Aribarg & Schwartz, 2020; Wang et al., 2019). Rather than delivering ads in traditional ad space, these "in-feed" placements deliver ad content directly into the publisher's news feed, ensuring that the ad content is surrounded by editorial content. These new display options have significantly increased the complexity of digital display campaigns to the extent that the Interactive Advertising Bureau published a native advertising playbook to help advertisers understand the serving options (IAB, 2013). To highlight how these various ad types and ad placements are operationalized, Fig. 1 presents a screenshot of a landing page from US Weekly's home page where we highlight the various ad types.

While the distinction between in-ad and in-feed placements may seem trivial, the display advertising literature suggests that ad placement could have a dramatic effect on consumer response. The rationale behind this approach is grounded in the concept of "banner blindness," where consumers, annoyed with traditional display ads (Cho & Cheon, 2004), learn to avoid areas of the webpage that are typically associated with advertising (Dreze and Hussherr 2003; Chatterjee, 2008). Considering that in-ad placements are delivered in traditional ad space, the ad avoidance literature would suggest that—despite matching the form and function of the publisher's website—consumers may be negatively predisposed to the space the ad is placed in and be less inclined to click on it (Wang et al., 2019).

By camouflaging ads within editorial content, in-feed placements should be less susceptible to "banner blindness," perhaps giving them a better chance to be processed by the consumer rather than ignored. In fact, recent research indicates that in-feed placements are processed similarly to editorial content (e.g., news headlines), which makes them more likely to be clicked on than traditional banner ads (Aribarg & Schwartz, 2020). Taken together, the literature suggests that native display ads are most effective at addressing "banner blindness" when ads are not only visually similar to the publisher's content (e.g., color scheme, fonts, etc.) but also surrounded by publisher content. Accordingly, we propose the following:

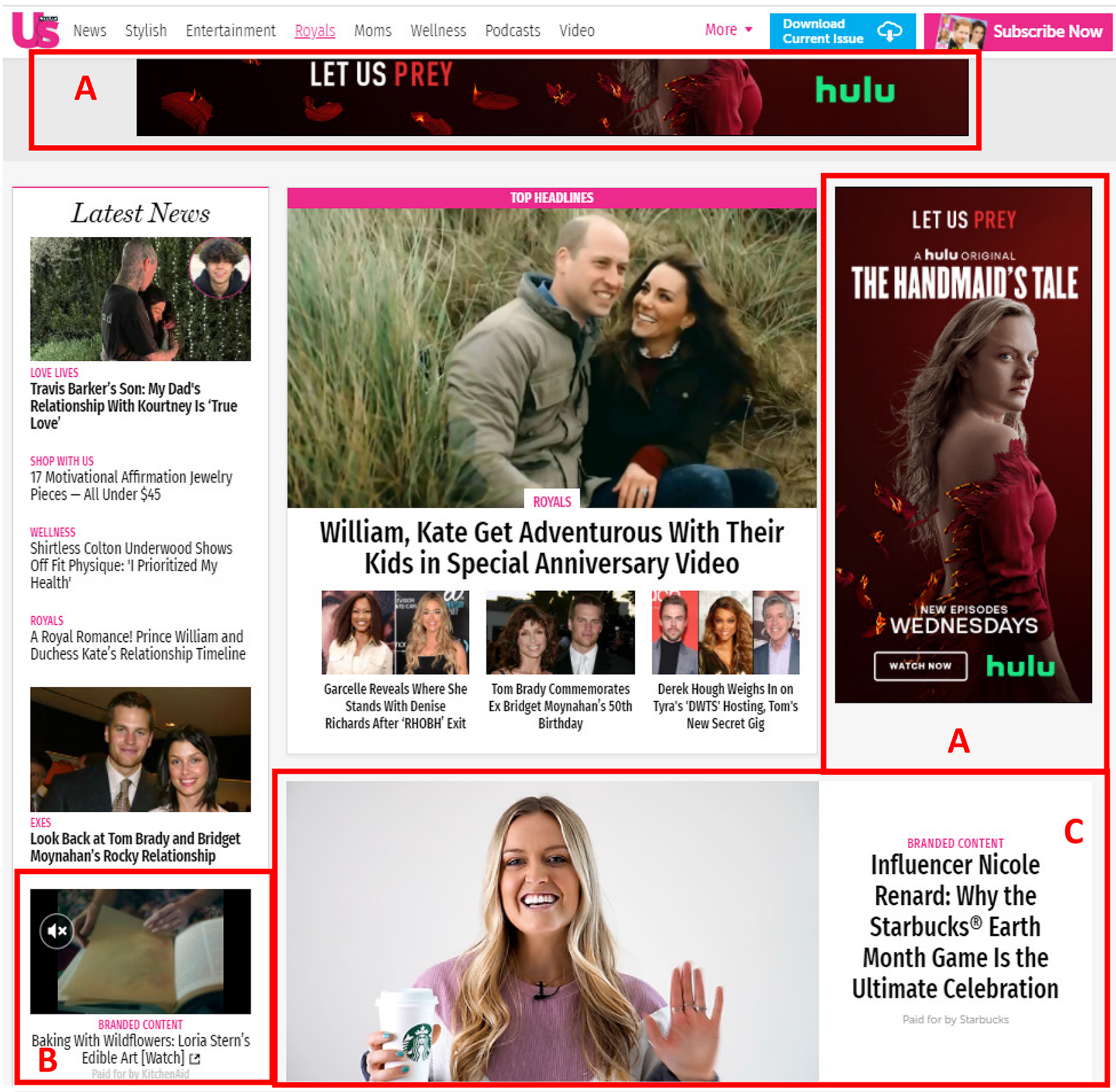
H1a Native in-feed placements experience more clicks than in-ad placements.

While the proximity of in-feed placements to surrounding editorial content might mitigate the issues of "banner blindness," researchers have cautioned that these placements "may 'postpone' annoyance to later stages of the online sales funnel (from pre-click to post-click)" (Wang et al., 2019, p. 84). The conspicuous presence of traditional display ads makes it relatively easier disengage with ad content (i.e., avoiding that area of the webpage) *before* clicking (Drèze & Hussherr, 2003; Chatterjee, 2008). In contrast, in-feed placements are designed to appear similar to editorial content, which a consumer might not immediately recognize as advertising (Aribarg & Schwartz, 2020). However, upon being redirected to the advertiser's landing page and ultimately revealing the promotional intent, the consumer should become annoyed if they were not expecting advertising content (Wojdynski & Evans, 2016). Given a redirection from a publisher's website to an advertiser's website, this revelation should occur within seconds of the landing page loading. As the consumer is unable to unclick the ad, the only action to avoid the ad content is to exit the website. Such an immediate disengagement would be considered a bounce, where the consumer exits the landing page without interacting with any of the content (Edwards, Li, & Lee, 2002).

H1b Native in-feed placements experience more bounces than in-ad placements.

Our hypotheses argue that consumers directed from in-feed placements to the advertiser's website are more likely to bounce from the landing page because they become annoyed upon realizing the content on the landing page is promotional rather than editorial (Wang et al., 2019; Wojdynski, 2016). In these instances, the bounce decision by a consumer is driven by these negative feelings associated with having their browsing experience intruded upon by an advertiser and they will be motivated to immediately disengage with the advertiser by bouncing from the advertiser's website.

The notion that annoyance mediates the effect of in-feed placement on bounces is consistent with prior advertising research (Campbell, 1995; Hu & Wise, 2021; Li & Meeds, 2007). Recent studies have shown that when advertising disrupts a consumer's browsing task, it triggers the consumer



A – Traditional banner ads displayed at the top of the page in a format consistent with the advertised brand rather than the publisher's site.
B – In-feed, native ads shown alongside editorial content in a format consistent with the publisher's content.
C – In-ad, native ad served in a format consistent with publisher's site.

Fig. 1 Examples of native and traditional display ads from usmagazine.com

to restore control by closing the ad or leaving the publisher's website (Hu & Wise, 2021; Li & Meeds, 2007). Similarly, when consumers believe they have been tricked by an ad, they become annoyed with the advertiser, which ultimately leads to diminished attitudes and future purchase intentions (Campbell, 1995). Thus, we suggest annoyance mediates the relationship between ad placement and bounces.

H2 Post-click consumer annoyance mediates the relationship between native ad placement (in-feed versus in-ad) and bounces.

Moderators of ad placement

Display ad content

To date, much of the research on native advertising has focused on how disclosures can more clearly distinguish native ads from editorial content (see Table 1). While disclosures undoubtedly facilitate ad recognition, why can't the same be said for ad content? Consider the following two headlines—"Talking Chop: Which Chef's Knife is Best for You?" versus "Shop Chef's Knives: Up to 70%

Off!"—which one is more likely to be perceived as an advertisement? Clearly, the latter option. However, among the research that has empirically tested the effects of in-feed placements on objective measures of ad performance, the content of the ads has not been considered (e.g., Aribarg & Schwartz, 2020; Wang et al., 2019). Furthermore, in the case of the Aribarg and Schwartz paper, all of the ads used in Studies 1 and 2 did not mention any sort of product promotion (Aribarg & Schwartz, 2020, p. 24). Rather, the ads in their studies all read similarly to headlines for news articles. The lack of selling intent in the ad headlines could perhaps explain why the in-feed native ads generated much higher clicks than the traditional display ad. Thus, it is not clear if it is the ad placement, ad content, or both impact clicks.

Native ads high in selling intent will likely lose some of their ability to blend in versus native ads low in selling intent. The promotion focus differs from the browsing goals of consumers reading through the publisher's website content. Thus, consumers will mentally flag it as an ad compared to an ad designed to be low in selling intent. If the browsing goals of consumers are violated, it will feel more intrusive. From the annoyance effect perspective, we argue that selling intent will moderate the effect of native ad placement on clicks. Given that in-feed placements benefit from their "visual resemblance… to the surrounding content" (Aribarg & Schwartz, 2020, p. 24), the positive effects of visual resemblance on clicks should be particularly strong when selling intent is low (i.e., the ad reads more like a news article headline). However, when the selling intent of the ad is high, pre-click annoyance should increase, particularly for in-feed placements, which reduces clicks. Thus, we expect that clicks will be higher (lower) for in-feed placements when the selling intent of the ad is low (high).

H3 The positive effect of native in-feed (versus in-ad) placements on clicks is moderated by selling intent such that the effect is stronger (weaker) when ad selling intent is low (high).

Landing page content

Extending beyond bounces, researchers have also noted that many questions remain as to "how advertisers should design…content that readers see after clicking on native ads" (Aribarg & Schwartz, 2020, p. 32). While publishers focus on getting clicks for their paying clients, advertisers are more concerned about consumers' activity once they arrive on the landing page. As hypothesized, consumers exposed to in-feed placements should exhibit relatively higher post-click annoyance, which increases the likelihood that they will bounce from the landing page. However, if consumers successfully mentally flagged the ad and still clicked on it, the redirect to advertiser content is likely congruent with their expectations and browsing goals. Thus, while we expect the redirection to a third-party website to affect consumers' initial reactions, we also believe that the selling intent of the landing page plays a vital role in determining the consumer's ultimate decision to digest the advertiser's content (or not and bounce).

To this end, Goyal et al. (2018) investigated how landing page content influenced consumer expectations and found that consumers who click on in-feed placements expect editorial content rather than promotional content. If consumers associated in-feed placements with editorial content, then perhaps advertisers should design content that appears relatively more editorial in nature. In this context, the landing page's selling intent is of particular relevance, largely because editorial content seldom attempts to sell a product or service. As a result, we argue that when in-feed placements are directed to a landing page with lower selling intent (e.g., a blog style article), the experience will be more congruent with consumers' desires from the clicking action and should mitigate the post-click annoyance brought on by in-feed placements.

H4 The effect of native in-feed placement (versus in-ad) on bounces will be weaker when the selling intent of the landing is low.

Redirection type

While display ads typically redirect ad clicks to landing pages on the advertiser's website, advertisers also might consider directing consumers to sponsored content within the publisher's domain (e.g., Wojdynski & Evans, 2016). This can be executed through microsites or advertorial content developed jointly between and advertiser and the publisher. For these types of re-directions, the consumer remains on the publisher's website. This consistent experience has a higher likelihood of being perceived as congruent with a consumer's browsing goals and should be viewed as less intrusive and annoying. On the other hand, redirection to the advertiser's website from an in-feed placement should amplify annoyance as the consumer has multiple, incongruent signals that they are now being directed away from their browsing goals and even the editorial content they were consuming. Accordingly, we contend that redirection (externally to an advertiser site vs. internally to a new landing page within the publisher's domain) will moderate the relationship between ad placement and annoyance:

H5 The effect of native in-feed (versus in-ad) placements on consumer annoyance is stronger when consumers are redirected to an advertiser-owned (publisher-owned) landing page.

Study 1: Evaluating the drivers of click-based effectiveness

Our first study investigates how advertiser decisions related to the content and placement of native display ads influence clicks. To test our hypotheses, we collaborated with one of the largest programmatic buy-side native advertising platforms in the United States.

Ad selection

Within their portfolio of clients' brands, we sought to identify brands that met a few key criteria for inclusion in our study. First, we targeted well-known consumer brands that are experienced in digital marketing to increase the likelihood of robust and calibrated digital campaigns. Second, we sought firms that regularly ran digital advertisements with both high and low selling intent appeals. Using the firm's database, we first searched for brands that deployed messages with higher levels of selling intent. Using regular expressions, we retrieved ad copies that mentioned (1) savings (e.g., "(save|save up to|savings up to) ([[:digit:]]+%|\\$[[:digit:]]+)"), (2) product releases (e.g., "(upgrad|remaster|next-generation|all-new|reinvent|the new)"), or (3) pricing (e.g., "free (shipping|returns)"). We then conducted a search for low selling intent ads. One expression used for this was "[[:digit:]]+(way|tip|secret|tricks|thing|hack|myth|factor|idea)." After cross-referencing the brands that were contained in both datasets, we identified three brands for deeper investigation. The first is an apparel brand that designs and sells shoes, clothing, and accessories for men and women, the second is a retailer that specializes in home furnishings and organization products, and the third is a cosmetics brand. For each brand, we reviewed their existing creative efforts and identified a subset of two high selling intent ad copies and two low selling intent ad copies, for a total of 12 unique ad copies.

After identifying the sample frame, we captured each advertisement's title, description, image, and other information using the firm's analytics platform. This provided us with a unique "campaign scenario" for each observation in our dataset. Consistent with Wang et al. (2019, p. 88), a campaign scenario (CS) "means a particular native ad viewed by a particular type of viewer under a particular circumstance." We recorded information about the ads including where it was served (in-feed versus in-ad), the week they were served, the viewing device, as well as bidding information. This resulted in an initial sample of 254,962 campaign scenarios. For each CS (i.e., for a native ad served on publisher p, to users of device type d, with a placement of f, during week t), we were provided the total number of impressions, clicks, placement cost, and number of bids by the advertiser. Across 13,062 publishing websites, the twelve ads received over 100 million impressions and over 60,000 clicks, with an average placement cost of $0.89.

Ad coding

Prior to running our analyses, we needed to assess whether the twelve advertisements truly conveyed differing levels of selling intent. To do this, we adopted two different coding approaches. First, we recruited a panel of participants from Centiment at a cost of $4.75 per participant. Coders were located in the U.S. and were blind to our hypotheses. Upon receiving detailed instructions, the panelists were then shown the ads similar to how it would be displayed on a website news feed—with the image and a bolded headline above the description text. To eliminate potential order effects, the order the ads were displayed in was randomized. For each advertisement, the coders then responded to a variety of content scales that have been adapted from the marketing and advertising literature. Specifically, selling intent was measured with four items from the scale used by Tutaj and van Reijmersdal (2012). A sample item is "The aim of this content is to sell me something" where 1 = Strongly Disagree and 5 = Strongly Agree.

While selling intent was the focal measure of interest, we also had the coders evaluate the ads based on overall emotion, emotion types (i.e., love, pride, guilt, and fear), and argument types (refute, compare, and unique positioning). For these alternative appeal types, we adopted the same approach as Chandy et al. (2001) by having coders simply indicating "0" if the ad did not suggest these feelings or arguments and "1" if they did. In addition to the ad content measures, we included attention check questions throughout the coding instrument (Oppenheimer et al., 2009). Specifically, we added math questions (e.g., 4 + 7 = 11) to disqualify respondents who did not provide correct answers to attention check questions and screened out participants based on overall completion time. Given the quality checks, we needed to recruit 150 participants from Centiment, to achieve our usable sample size target of 75, who provided data suitable for analysis.[1] We also validated the Centiment coding effort by recruiting three graduate assistants who were unfamiliar with the research to independently code the ads (Chandy et al., 2001). The results of the coding process resulted in similar classification of the ads (See Table 2).

[1] Given that the coders were required to code all twelve advertisements across a variety of scales, we believe that fatigue played a major role in coders not passing quality checks.

Table 2 Study 1 appeal types across ad copies

	Clicks	Impressions	Campaign Scenarios	Selling Intent: Centiment Raters[a]	Selling Intent: GA Raters[b]
Brand A – Clothing & Shoe Retailer					
High Selling Intent					
Ad 1A	2,364	4,374,040	21,767	4.42	4.75 (.86)
Ad 2A	3,606	5,239,704	20,043	4.26	4.67 (.82)
Low Selling Intent					
Ad 3A	8,309	18,642,925	55,173	2.31	1.08 (.95)
Ad 4A	4,487	13,261,909	58,827	2.36	1.00 (1.00)
Brand B – Home Storage & Furnishings					
High Selling Intent					
Ad 1B	697	2,241,663	8,356	4.14	4.33 (.77)
Ad 2B	258	721,046	3,895	4.20	4.50 (.71)
Low Selling Intent					
Ad 3B	289	408,573	6,967	3.16	2.58 (.55)
Ad 4B	264	416,152	7,026	3.71	3.75 (.51)
Brand C – Specialty Products & Cosmetics					
High Selling Intent					
Ad 1C	9,074	22,113,713	4,597	4.19	4.75 (.90)
Ad 2C	17,046	47,301,617	18,491	4.47	4.00 (.56)
Low Selling Intent					
Ad 3C	6,171	1,923,103	7,513	3.83	3.50 (.86)
Ad 4C	6,878	2,186,486	7,850	4.12	4.33 (.75)

[a]N = 75; Italicized cells indicate the value is significantly lower than both high selling intent ads ($p < .05$)

[b]N = 3; Raters were blind to our hypotheses. Interrater agreement across four scale items is shown in parentheses. The ICC for the ads in the dataset was .71

To assess the extent to which the ads differed on selling intent and the other ad appeal types, we conducted a series of mean comparisons using Tukey tests. Table 2 reports the means and standard errors resulting from the coding process as well as significance of these mean comparisons. The results demonstrate that for all but one of the ads in the sample, the low selling intent ads were consistently perceived as having lower selling intent than the high selling intent ads. Moreover, the ads did not differ with respect to the other appeal and argument types, which suggests that our model is likely to not be confounded due to other appeal types varying across conditions (for a more detailed analysis, see Web Appendix D). After removing the ad that did not pass the manipulation check, there were 212,655 unique CS in our sample.

Measurement

The coding process provided a clean operationalization for ad appeal where 1 = high selling intent and 0 = low selling intent. The remainder of the variables were measured based on data from the bidding platform. Similar to data utilized by Wang et al. (2019), the data used in this study is unique relative to most prior studies that have examined the performance of keyword-based advertising based on aggregated performance data that is typically visible to advertisers. Specifically, our data is sourced directly from the bidding platform responsible for the placement of the advertisements. Consequently, our campaign-level data offers precise measurement of cost, competition, and performance for each campaign on each domain in the sample. Moreover, the data provided is not hindered by measurement error associated with aggregated models of digital marketing effectiveness.

The placement of the ad was coded solely based on reporting from the bidding platform, where an in-feed placement = 1 and an in-ad placement = 0. For each CS, the bidding platform captured the total number of clicks and impressions. The descriptive statistics and correlations of these focal variables and additional covariates can be found in Table 3.

Endogeneity corrections

In addition to these variables of interest, we also captured data from the bidding platform to directly control for potential alternative explanations in a manner consistent with the robustness checks in Wang et al. (2019). Specifically, rather than making an indirect correction for potential bias from missing covariates, we sought to directly control for their influence. Specifically, we identified seven variables that

Table 3 Study 1 descriptive statistics and correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Bids	-								
(2) Clicks	.27	-							
(3) Contextual	.06	-.02	-						
(4) Cost	.39	.46	-.03	-					
(5) Impressions	.52	.51	-.02	.81	-				
(6) In-Feed	-.01	-.02	.14	-.03	-.04	-			
(7) High Selling Intent	.01	.04	-.23	.06	.08	.04	-		
(8) Mobile	-.01	.03	.01	.00	-.01	-.03	.13	-	
(9) Tablet	-.04	-.03	.23	-.03	-.05	.03	.14	-.10	-
Mean	6,031	.25	.35	1.01	549	.56	.36	.03	.27
S.D	64,426	3.46	.48	15.81	5,123	.50	.48	.16	.44

N = 212,655; Note: All correlations are significant at the .01 level with the exception of the correlation between Cost and Mobile (p = .337)

could confound our results: advertiser cost, competitive intensity, targeting, advertiser experience, temporal effects, quality of the publishing domain, and consumer device. Web Appendix E reviews each of these potential sources of omitted variable bias, the potential confound, and our empirical solution.

Model-free evidence

Before discussing the results of our formal model tests, we first provide model-free evidence for our proposed effects. Specifically, we begin by simply calculating the click-through rates (clicks/impressions) across ad appeal (low versus high selling intent) and ad placement (in-feed versus in-ad). Across all CS in our dataset, the average click-through rate was 0.045%. Consistent with H1a, click-through rates were higher for in-feed placements (0.054%) than in-ad placements (0.040%)—see bottom row of Table 4. Next, we undertook a preliminary look at the extent to which the ad placement effects were contingent on the ad type. The results provide directional support for our theorizing. For native ads with low levels of selling intent, click-through rate improved when the ads were delivered in-feed versus in-ad ($\Delta = +0.024\%$). On the contrary, ads exhibiting elevated levels of selling intent experienced a much smaller lift in click-through rate ($\Delta = +0.005\%$). Taken together, the results provide initial support for the effects outlined in H1a and H3. In the next section, we provide a more formal assessment of the hypotheses by modeling the effects of ad appeal and placement on clicks.

Model specification

Given the unique nature of the dependent variable—clicks—traditional OLS regression might not be appropriate. Previous research in digital advertising has modeled clicks by using the count of clicks as the dependent variable and accounting for impressions on the right side of the equation (Ghose et al., 2013; Stephen et al., 2015; Kireyev et al., 2016). Adopting a similar approach, our dependent variable is the number of clicks, with the number of impressions included as the exposure variable. While one might be tempted to model the clicks (λ_i) as a Poisson process, researchers have argued that one should allow for heterogeneity in λ_i by assuming that λ_i comes from a gamma distribution (Danaher, 2007). The Poisson-gamma mixture (negative binomial) distribution that results is

$$Pr(u_i, \alpha) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(y_i + 1)\Gamma(\alpha^{-1})}\left(\frac{1}{1 + \alpha\mu_i}\right)^{\alpha^{-1}}\left(\frac{\alpha\mu_i}{1 + \alpha\mu_i}\right)^{y_i}$$

where

$$\mu_i = X_i\mu$$
$$\alpha = \frac{1}{v}$$

The parameter μ is the mean incidence rate of y per unit of exposure. X_i is used to denote the number of impressions

Table 4 Study 1 model-free evidence of click-through rates by selling intent and ad placement

		Native Ad Placement			
		In-Ad	In-Feed	Overall	Δ
Selling Intent	**Low**	.0445% (61,951)	.0682% (73,555)	.0563% (135,506)	+.0237%
	High	.0387% (31,726)	.0437% (45,423)	.0403% (77,149)	+.0050%
	Overall	.0401% (93,677)	.0536% (118,978)	.0451% (212,655)	+.0135%

The number of campaign scenarios for each cell is given in parentheses. Δ indicates the difference in click-through rate for in-feed placements relative to in-ad placements.

Table 5 Study 1 parameter estimates using a binary operationalization of selling intent

	Main Effects				Full Model			
Variable	Estimate		S.E	Z	Estimate		S.E	Z
Focal Variables								
In-Feed	.35	***	.02	18.45	.43	***	.02	17.81
High Selling Intent (HSI)	.11	***	.03	4.47	.25	***	.04	6.88
In-Feed × HSI					-.18	***	.03	-5.15
Other Parameters								
Intercept	-8.68	***	.16	-52.99	-8.84	***	.16	-54.96
Mobile	1.26	***	.04	28.90	1.20	***	.04	33.87
Tablet	1.10	***	.02	44.41	1.08	***	.02	45.00
Contextual Targeting	-.46	***	.03	-14.33	-.45	***	.03	-14.27
Placement Cost	.00	**	.00	2.09	.00	**	.00	2.30
ln(Bids)	.01		.01	.96	.01		.01	1.45
Brand B	-.17	***	.05	-3.78	-.18	***	.05	-3.98
Brand C	.23	***	.06	3.85	.27	***	.05	5.18
Domain Supply Tier 2	-.05		.14	-.36	-.05		.14	-.35
Domain Supply Tier 3	-.04		.14	-.31	-.03		.13	-.24
Domain Supply Tier 4	.64	***	.15	4.36	.66	***	.15	4.55
Domain Supply Tier 5	.58	*	.34	1.70	.70	**	.33	2.08
Weekly Fixed Effects	Included				Included			
Model Accuracy								
AIC	88,748.2				88,719.9			
BIC	89,107.5				89,089.5			
LogLik	-44,339.1				-44,323.9			
Δ Chi Square					30.31***			

N = 212,655; *** $p<.01$, ** $p<.05$, * $p<.10$

for observation i. As the mean of y is determined by the number of impressions and a set of k regressor variables, we use the following expression to relate these quantities.

$$\mu_i = exp(ln\left(X_i\right) + \alpha_0 + \beta_1 InFeed + \beta_2 HSI + \beta_3 InFeed \times HSI + \gamma\delta + u_d)$$

In estimating the rate ratio (μ_i), α_0 refers to the global intercept. *InFeed* is a dummy variable indicating whether the ad is an in-feed placement. *HSI* is a dummy variable indicating a high selling intent ad. We capture the moderating effect of ad placement on ad appeal through the interaction terms with *InFeed* × *HSI* variable. δ is the vector of control variables. Finally, given that advertising response could be influenced by unobserved factors related to the publisher, we allow α_0 to vary by estimating random intercepts for the publishing domain (u_d). Ultimately, this modeling approach allows for our estimation of clicks to be akin to predicting click-through rate as we condition on total impressions.

Results

We present the results of our analysis in Table 5. Given the contingent nature of the moderation effects proposed in the first study, we first estimated an equation for the main effects. Then, to explore our interactions, we present our full model.

Effects of native ad placement

For H1a, we predicted that in-feed placement would be more effective in generating clicks than in-ad placements. As the coefficient for in-feed was positive and significant ($\beta = 0.35$, Z: 18.55, $p < 0.001$), we find support for H1a. Thus, we conclude that when holding other variables constant, in-feed placements are more efficient in generating clicks than ads served in traditional ad space (i.e., in-feed placements require fewer impressions to generate the same number of clicks). In addition to the main effect of

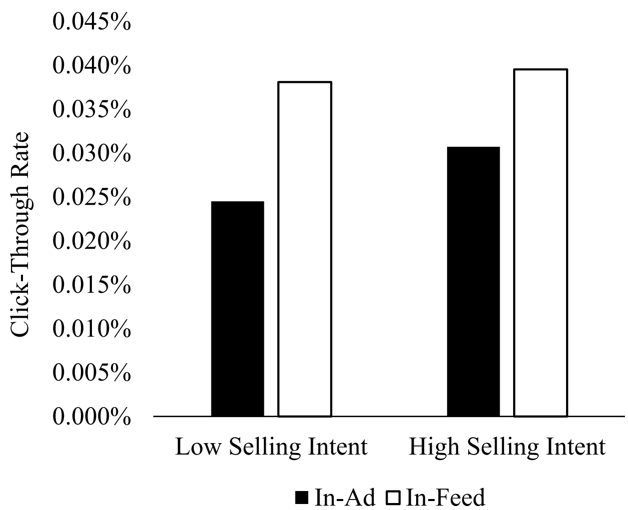


Fig. 2 Study 1 interaction plot of native ad placement and selling intent

ad placement, the main effect for the high selling intent dummy variable was also significant ($\beta = 0.11$, Z: 4.47, $p < 0.001$), suggesting that, ceteris paribus, ads higher in selling intent experience greater clicks compared to low selling intent ads.

Moderating effect of ad content

For H3, we predicted that ad content would interact with ad placement to the extent that the placement effect on clicks would be weaker (stronger) for ads with high (low) selling intent. As the estimate for the interaction term was both negative and significant ($\beta = -0.18$, Z: -5.15, $p < 0.001$), we find support for H3. More specifically, we find that the positive effect of an in-feed placement remains significant but is weakened when the ad contains high levels of selling intent. This is shown graphically in Fig. 2.

Robustness checks

To ensure that our results were not an artifact of the measurement of our variables, we ran additional models using the continuous measure of selling intent from the human coding process, where lowest levels of selling intent held a value of 1 and the highest values of selling intent held a value of 5. Consistent with H1a, the parameter for ad placement was similar in size and magnitude ($\beta = 0.34$, Z: 18.13, $p < 0.001$). We observed a similar pattern for the interaction term as well ($\beta = -0.05$, Z: -5.01, $p < 0.001$). Consequently, we are confident that our results do not stem from the operationalization of our appeal. Full model results of the robustness tests are presented in Web Appendix F.[2]

Discussion

Our results demonstrate that in-feed placements are associated with a higher likelihood of being clicked. When observing the main effect of native ad placement, our results suggest that when holding other factors constant, in-feed placements are about 42% (i.e., $e^{.35} = 1.419$) more likely to be clicked on than in-ad placements. This is a particularly impactful finding given that we explicitly control for the cost of the placement in estimating our model.

Our findings also reveal that clicks are driven by more than just native ad placement. The content of native advertisements is also important. Given the centrality of selling intent in digital advertising messages, it is notable that we are the first to explicitly test the influence of message selling intent of native display ads. Looking strictly at main effects, we find that native ads containing explicitly commercial content (e.g., offers a discount or promotes a sale) tend to perform better than ads that convey little selling intent. This is unsurprising, as these ads are explicitly incentivizing the consumer to get a product at a discounted price. When taking a closer look at the interaction between selling intent and ad placement, we find that placement effects are relatively stronger (weaker) for low (high) selling intent ads. This suggests that there are interplays that impact the relative effectiveness of ad content and ad placement.

Study 2: The drivers of post-click effectiveness

The results of our first study provide unique insight into what drives clicks for native ads. However, there has been a call for research on what happens *after* consumers click on native ads (Aribarg & Schwartz, 2020, p. 32). While Wang et al. (2019) provide initial evidence for delayed post-click annoyance, it is important to pinpoint how early in the customer journey annoyance is triggered. To address this issue, we conducted a field experiment with a fitness center that is based out of a large city in the Northeastern United States. The goal was to examine how native ad placement and landing page content influence a consumer's likelihood

[2] In addition to this assessment, we also re-estimated the models using continuous scores from the graduate assistant coding process and the results were also consistent. Consequently, the choice of coders did not influence our results.

of bouncing. We also conduct a supplemental examination of the relative clicks between in-feed and in-ad placements.

Experimental design

To develop the manipulations for our experiment, we created two unique landing pages for the fitness center: a low selling intent landing page and a high selling intent landing page. Both pages were not directly linked to by any other pages on the website. The low selling landing page was written in a blog-style format that was developed with direct input from the fitness center's head trainer and marketing team. The page provided informative content on how to change up a workout routine at the beginning and concluded with a call to action for readers to sign up for a free three-day pass at the fitness center. The high selling intent landing page was a splash page featuring promotional headlines and a form to sign up for a free three-day pass at the fitness center. It is important to note while the selling intent of each landing page differed, the conversion goal of the campaign—to get readers to sign up for a free three-day pass—remained the same. A pretest of these landing page manipulations revealed that while the landing pages differed in selling intent, there were no significant differences in perceptions of website quality. More information on the manipulations and the pretest can be found in Web Appendix G.

Given the primary focus on post-click effectiveness measures, we created the same ad copy for both landing pages (i.e., the image and headline were the same for each page). In choosing the appeal type for the ad copy, we opted to focus on low selling intent appeals to extend the research by Aribarg and Schwartz (2020). The headline read, "Stuck in a Routine? Here are 10 Tips to Break Out of a Fitness Rut!" Given the content of the headline, we anticipate that those who click on the ad will be expecting to visit a page that offers tips to switch up their workout routine (i.e., the low selling intent landing page). We expect consumers directed from in-feed placements to exhibit relatively more negative post-click behaviors than those directed from in-ad placements. However, for consumers directed from in-feed placements to the low selling intent page, we expect these adverse effects of ad placement to be attenuated.

Method

We partnered with the same native advertising platform from Study 1 to create and run our native advertising campaigns. As mentioned previously, the campaigns all contained the same image and headline to ensure minimal differences in the evaluation of the ad content before the click. However, we did manipulate whether the ad was in-feed or in-ad, resulting in a 2 (Native Ad Placement: In-Feed versus In-Ad) × 2 (Landing Page Selling Intent: Low versus High) research design.

Given that the fitness center we were working with operated regionally, we targeted the Designated Marketing Area (DMA) of the metropolitan area where all of the firm's franchises were located. However, to ensure that the exposure for each of the conditions was as randomized as possible, we took several steps. First, we did not employ any further targeting for location (e.g., zip code), device, or users' interests. Second, we had the native advertising platform disable all of their creative optimization algorithms to ensure that each cell accumulated similar and randomized exposure. Disabling these features supports the random assignment of the experimental conditions, which can effectively remove the risks of endogeneity bias when interpreting the primary effects of the field experiment (Rutz & Watson, 2019). With these controls in place, we ran the experiment for three weeks.

Model-free evidence

Upon the completion of our experiment, we collected both click-stream data from the native advertising platform and session-level data from the fitness center's website analytics platform. Across all conditions, there were over 600,000 impressions that generated 1,387 clicks (maximum cost per click was set at $2.00 based on recommendations from our partner firm). The data allowed us to track sessions across stages of the digital customer journey (i.e., impression → click → landing page load → bounce decision → site visit) to provide a more complete review of the relative performance of in-feed and in-ad placements before and after the initial click. Each of the four conditions generated between 336 and 353 clicks and click-through rates were higher for in-feed placements than in-ad placements (0.26% vs 0.20%, $\chi^2 = 20.78$, $p < 0.01$). According to the native advertising platform's clickstream data, 70.3% of clicks resulted in the landing page loading (969 unique sessions). This is not surprising as many consumers will mistakenly click ad content and exit before the landing page is fully loaded.

For each session, a bounce was recorded if the user left the page before interacting with the page (Google, 2023). Across the 969 unique sessions, there were 592 bounces, which amounts to a bounce rate of 61.1%. Consistent with our theorizing for H1b, bounce rate was higher for users directed from in-feed placements than those directed from in-ad placements (67% vs. 54%, $\chi^2 = 17.21$, $p < 0.01$).

Table 6 Study 2 model free results

	Metric	Operationalization	Ad Type	
			In-Feed	In-Ad
Publisher Website	**Impressions**	Number of times a given ad was served across the field experiment	268,846	337,811
	Clicks	Total clicks on a served ad	699	679
	CTR	Click-through Rate (Clicks / Impressions)	0.26%	0.20%
	Cost Per Click	Average Cost Per Click^	$1.93	$1.94
	Total Cost	Total Cost of Campaign (Clicks*Cost Per Click)	$1,349	$1,319
Advertiser Website	**Landing Page Loads**	Count of consumers who clicked an ad and did not exit the advertiser's site before it loaded	519	450
	Bounce Rate	Percentage of customers who exited the advertiser page before interacting with content	67.20%	54.00%
	Net Visits	Count of consumer visits where the user interacted with the advertiser site (Landing Page Loads*(1-Bounce Rate))	170	207
	Net Visit Percentage	Percentage of consumers who were exposed to an ad who eventually were counted as a net visit (Net Visits / Impressions)	0.063%	0.061%
	Cost Per Net Visit	Cost per advertiser site visitor	$7.39	$6.37

Table 7 Study 2 descriptive statistics and correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Bounce	-							
(2) Low Selling Intent	.02	-						
(3) Hour	.05**	-.04	-					
(4) In-Feed	.14***	.00	.04	-				
(5) Mobile	-.02	-.02	.01	-.17***	-			
(6) Net Visit	-.53***	.01	-.03	-.07***	-.13***	-		
(7) Tablet	.05*	-.00	-.01	.10***	-.45***	.00	-	
(8) Weekday	-.02	.07***	.03	.01	-.06**	.09***	-.08***	-
Mean	.43	.51	13.75	.51	.78	.27	.05	.72
S.D	.49	.50	5.93	.50	.42	.44	.23	.45

N = 1,387; *** $p < .01$, ** $p < .05$, * $p < .10$

However, we did not find significant differences in bounce rate when probing the interaction between landing page selling intent and ad placement ($\chi^2 = 0.01$, $p > 0.50$), failing to support H3. Finally, we assessed how many sessions resulted in a net visit (i.e., they did not bounce) and we found comparable net visit rates across in-feed and in-ad placements (0.063% vs. 0.061%, $\chi^2 = 0.092$, $p = 0.76$).

Taken together, these results show a nuanced path by which in-feed and in-ad placements impact customer behavior. Specifically, we find that in-feed ads once again experience a higher click-through rate (consistent with H1a), but they also experience a higher bounce rate (consistent with H1b). Collectively, this results in comparable net visit rates across in-feed and in-ad placements. Simply put, in-feed and in-ad placements were equally effective in converting impressions into site visits. While not formally hypothesized, we also find that the average cost per visit is 16% higher for in-feed versus in-ad placements ($7.39 vs. $6.37). Model-free results as well as cost data are provided in Table 6.

Model testing

To empirically test our hypotheses, we focused on three metrics: clicks (validation of H1a), bounces (initial test of H1b—main effect and H4—moderating effect of selling intent of the landing page), and net visits (exploratory assessment). As mentioned previously, a click simply captures if a consumer clicks on an ad from the publisher's site. A bounce is recorded when the landing page loads and the consumer leaves the page without interacting with the webpage (i.e., scrolling, clicking in the browser window). Net visits capture sessions where a consumer interacts with the landing page.

We adopt a similar modeling approach to that used in Study 1. Specifically, we identify an exposure variable on the right side of the equation for our three outcomes of interest. For clicks and net visits, we employ total impressions as the exposure variable, so we can assess clicks and

Table 8 Study 2 parameter estimates for clicks, bounces, and net visits

	Clicks[a]		Bounces[b]				Net Visits[a]			
	(1)		(1)		(2)		(1)		(2)	
	Est	S.E	Est	S.E	Est	S.E	Est	S.E	Est	S.E
Focal Variables										
In-Feed	.18**	.09	.38***	.08	.35***	.12	-.04	.17	.05	.21
Low Selling Intent			.03	.08	.01	.12	.05	.11	.13	.15
In-Feed × Low Selling Intent					.05	.17			-.18	.23
Other Parameters										
Mobile	.86***	.09	.37***	.10	.37***	.10	.20	.16	.20	.16
Tablet	.43***	.15	.33	.19	.33	.19	.03	.25	.04	.25
Weekday	-.01	.18	-.23*	.10	-.23*	.10	.33**	.14	.33**	.14
Hour	Fixed		.01	.01	.01	.01	Fixed		Fixed	
Domain Name	Fixed						Fixed		Fixed	
Model Fit Statistics										
AIC	9,990.3		1,268.6		1,270.5		4,343.9		4,345.3	

*** $p < .01$, ** $p < .05$, * $p < .10$

[a]Conditioned on Impressions

[b]Conditioned on Landing Page Loads

visits accounting for impressions, which allows a "head-to-head" assessment of the relative probability of our two ad placements resulting in initial clicks as well as final visits to an advertiser website. For bounces, we adopt clicks as the exposure variable, so we can assess the probability of a bounce given that a session had clicked on an ad. All variables are modeled as binary outcomes using a probit link function.

We also include a series of covariates in the models including user device (e.g., mobile, desktop, tablet) as well as the date and time of the visit. The values for device type, ad placement, and landing page were all converted into dummy variables. To control for possible temporal effects, we also coded a dummy for whether the visit occurred on a weekend or weekday and measure for the time of day. The descriptive statistics for the variables used in our analysis can be found in Table 7.

Results

For clicks, the selling intent of the landing page is irrelevant, so we exclude the selling intent variable as well as its interaction with ad placement and estimate one main model with the covariates. For the other two variables, the first model presents the main effects, while the second presents the full model with interactions. Complete results are provided in Table 8.

Effects of ad placement

H1a proposed that in-feed ads would experience more clicks than in-ad placements. Our results supported this hypothesis as consumers directed from in-feed placements were more likely to click on the ad ($\beta = 0.18$, t: 2.00, $p < 0.05$). In H1b, we predicted that users directed from in-feed placements would exhibit relatively higher bounces. Consistent with our predictions, consumers directed from in-feed placements were more likely to bounce from the landing page ($\beta = 0.38$, t: 4.54, $p < 0.01$). Thus, we find support for H1b. Finally, we conducted an exploratory test on net visits to assess the extent to which the competing click and bounce effects offset each other. For net visits, we find no difference between in-feed and in-ad placements ($\beta = -0.04$, t: -0.24, $p > 0.05$).

Contingent effects of landing page content

For H4, we predicted that the low selling intent landing page would weaken the effect of ad placement on bounces. However, as the interaction term was not significant for bounces ($\beta = 0.05$, t: 0.30, $p > 0.20$) or net visits ($\beta = -0.07$, t: -0.488, $p < 0.01$), we do not find support for this hypothesis. This result suggests that the higher bounces experienced by in-feed placements could not be buffered by the landing page, which suggests that annoyance from being redirected after clicking on an in-feed ad is immediate.

Discussion

The results of our field experiment replicate and extend the results of the first study. First, we demonstrate that in-feed placements once again experience higher clicks, replicating Study 1 results. Then, we extend these results by exploring what happens after consumers click on a native ad. Consistent with the annoyance effect proposed by Wang et al. (2019), we find that consumers directed from in-feed placements were more likely to bounce from the landing page than those directed from in-ad placements. Thus, it appears that for in-feed placements, the improvement in clicks that we found in Study 1 could be offset by diminished post-click performance. In fact, our examination of net visits across in-feed and in-ad placements demonstrated no significant difference between these ad placements.

Although we hypothesized that the selling intent of landing page content would attenuate the effect of ad placement on bounces, we did not find support for this argument. Despite the editorial appearance of the low selling intent landing page, it experienced similar bounces. One explanation for why this may occur is the redirection effect, such that being redirected to an advertiser's website triggers post-click annoyance. To more directly test the process behind our findings, we developed a third study.

Study 3: Assessing the role of post-click annoyance

In this final study, we had three main goals. First, we wanted to test the hypothesized mechanism behind these effects—namely, whether consumer annoyance induced by native ad placement drives bounce intentions. Second, while most display ads redirect to advertiser-owned landing pages, we wanted to test whether annoyance is mitigated by directing consumers to sponsored content on the publisher-owned landing pages. Finally, we explore the extent to which feelings of annoyance can spillover and impact advertiser purchase intentions.

Research design

To test H2 and H5, we developed a two-factor, between subjects experiment: 2 (Ad Type: In-Feed versus In-Ad) × 2 (Landing Page: Redirect to Advertiser Page, Redirect to Publisher Page). As the baseline scenario, we revised a screen capture of the USNews.com landing page and asked participants to imagine they were browsing U.S. News. For the advertiser, we selected Wayfair as the focal brand as it was a well-known brand in a category conducive for low-selling intent appeals. The manipulated publisher page included an area for a banner ad at the top (i.e., in-ad placement) and an in-feed placement among the editorial content. This in-feed area was accompanied by the standard "branded content" disclaimer below the headline. We then used these areas to manipulate the type of ad that was served to participants. The headlines for both in-ad and in-feed placements were the same" "How to Decorate an Apartment like a Pro." For the in-ad manipulation, a banner ad designed based on Wayfair's current banner ad creative was featured at the top of the page and a filler advertisement for the United Way was placed in the "in-feed" section of the page. For the in-feed manipulation, a United Way banner ad was placed at the top of the page and in the in-feed section, we included the focal advertisement from Wayfair that included the same headline as the banner ad.

Across both ad-type conditions, we informed participants that they noticed the headline referenced in both ads and decided to click on it. Participants were again randomly assigned to one of two conditions at this stage. Specifically, in the redirect to the publisher site condition, participants were redirected to sponsored content on U.S. News' website. In the redirect to the advertiser's site condition, the participant was redirected to the same article on the advertiser's website.[3] The two publisher pages as well as the two landing pages that served as the experimental manipulations are included in Web Appendix H.

After viewing the redirected manipulations, participants continued to answer a series of survey questions. First, we assessed their intentions (yes versus no) to immediately leave the page (i.e., bounce). Participants were coded as bounces where 1 = bounce and 0 = stayed on the page. Then, we assessed their annoyance using a three-item scale based on Kronrod and Huber (2019). Finally, respondents were given a three-item scale regarding their future purchase intentions from the advertising brand (Umashankar, Ward, & Dahl, 2017). All measures are included in Web Appendix K. Two attention checks flagged 36 participants who were removed from the sample, resulting in a final sample size of 364.

Results

As an initial test of the relationships between ad type, landing page, and annoyance, we conducted an ANOVA analysis. Results revealed that consumers experienced

[3] A pre-test ($N = 100$) demonstrated that consumers perceived no significant difference in perceived selling intent between the US News Landing Page and the Wayfair landing page ($M_{USNEWS} = 5.17$; $M_{WAYFAIR} = 5.46$, $p = 0.46$), which provides support that any differences in bounce is not likely due to differences in selling intent.

higher annoyance from In-Feed versus In-Ad placements ($M_{\text{In-Feed}} = 3.85$, $M_{\text{In-Ad}} = 3.22$; $F = 8.79$, $p < 0.01$). Moreover, annoyance was higher following a re-direct to the advertiser web page ($M_{\text{AdvertiserPage}} = 3.76$, $M_{\text{PublisherPage}} = 3.31$; $F = 4.50$, $p = 0.04$). The two-way interaction between Ad Type and Landing Page ($F = 7.52$, $p = 0.006$) indicated that participants were more likely to experience an increase in annoyance when they were re-directed to the advertiser's page after clicking on an in-feed ad. Looking at simple effects, when consumers were served an ad in-feed, annoyance increased significantly when they were re-directed to an advertiser's page ($M_{\text{AdvertiserPage}} = 4.36$, $M_{\text{PublisherPage}} = 3.33$; $F = 11.98$, $p < 0.01$). However, when participants were served an ad in-ad, there was no difference in annoyance across the landing page conditions ($M_{\text{AdvertiserPage}} = 3.15$, $M_{\text{PublisherPage}} = 3.28$; $F = 0.19$, $p = 0.66$). The results demonstrated that annoyance is triggered when consumers are re-directed from in-feed ads to an external, advertiser landing page.

To more formally test our proposed conditional process analysis,, we estimated models using PROCESS model 7 (Hayes, 2012). In our analysis, the independent variable was native ad placement (1 = in-feed; 0 = in-ad), the moderator was redirection type (1 = advertiser-owned; 0 = publisher-owned), the mediator was annoyance, and the dependent variable was bounce intentions (1 = bounce; 0 = stay on landing page). We also ran a model with purchase intentions as the dependent variable.

In the first stage of the model, neither in-feed ad placement ($B = 0.05$, $SE = 0.30$, $p = 0.87$) nor redirecting to the advertiser's website ($B = -0.13$, $SE = 0.30$, $p = 0.66$) significantly affected annoyance. However, we found a significant interaction between these two factors ($B = 1.16$, $SE = 0.42$, $p < 0.01$). Probing the interaction revealed that the effect of in-feed placement was contingent on the nature of the redirect. Specifically, the conditional effects revealed that when an in-feed placement (versus in-ad) redirected the consumer to a landing page on the publisher's site, there was no increase in annoyance ($B = 0.05$, $SE = 0.30$, $p = 0.87$), thus consumers experienced comparable levels of annoyance when redirected internally across in-feed and in-ad placements. However, when redirected from an in-feed (versus in-ad) placement to the advertiser's page, consumer annoyance significantly increased ($B = 1.21$, $SE = 0.30$, $p < 0.01$. These results are consistent with H5.

In the second stage of the models (predicting bounce intentions and purchase intentions), annoyance affected both bounce intentions ($B = 0.94$, $SE = 0.09$, $p < 0.01$) and purchase intentions ($B = -0.26$, $SE = 0.03$, $p < 0.01$). In-feed ad placement did not affect either bounce intentions ($B = -0.10$, $SE = 0.29$, $p = 0.73$) or purchase intentions ($B = -0.13$, $SE = 0.12$, $p = 0.28$). With respect to assessing the moderated mediation effects implied in H2 and H5, we find support for moderated mediation for both bounce intentions (*Index of Moderated Mediation* = 1.09, $SE = 0.42$, $LLCI = 0.31$, $ULCI = 1.96$) and purchase intentions (*Index of Moderated Mediation* = -0.31, $SE = 0.11$, $LLCI = -0.54$, $ULCI = -0.09$). With respect to conditional indirect effects, we find that annoyance mediates the effect of in-feed (versus in-ad) placements on bounce intentions only when a consumer is redirected to the advertiser's website ($B = 1.14$, $SE = 0.32$, $LLCI = 0.54$, $ULCI = 1.84$). A similar pattern emerged for the indirect effect on purchase intentions where annoyance only mediated the effect of in-feed placements on purchase intentions when the consumer was redirected to the advertiser's site ($B = -0.32$, $SE = 0.09$, $LLCI = -0.50$, $ULCI = -0.15$). Ultimately, these results provide support for the pattern of results proposed in H2 and H5. Specifically, when consumers are redirected externally to an advertiser's site after clicking on an in-feed placement, they experience higher levels of annoyance, which spills over to increased bounce intentions and reduced future purchase intentions.

General discussion

As consumers have become increasingly skeptical and dissatisfied with traditional banner ads, publishers and advertisers alike have shifted their efforts toward native advertising. Despite the growing interest and investment in native advertising, past research has focused on investigating the impact of native advertising disclosures rather than exploring the influence of advertiser-controlled factors. Through our three studies, we aimed to explore the drivers of native ad performance across multiple stages of the customer journey. In Study 1, we leveraged a unique dataset to identify the drivers of click-based effectiveness. In Study 2, we ran a field experiment to replicate pre-click results from Study 1 and explore how consumers behave after clicking on a native advertisement. Then, in Study 3, we demonstrate that post-click annoyance due to a redirect to an advertiser's site is what drives changes in post-click behavior. We discuss the implications of our research in the following sections.

Managerial implications

Our findings provide evidence of the drivers of native advertising effectiveness and offer insight into how native advertising campaigns could best be designed. This section discusses how managers could design more effective native advertising campaigns.

Pros and cons of in-feed placements

Investment in native advertising has increased by over 400% since 2016 and has overtaken traditional banner advertising (eMarketer, 2022). Advertisers have driven this increase in pursuit of more consistent clicks and overall advertising performance. Despite this rapid investment and interest in native ads, our results suggest that the placement of these ads offer advertisers different performance outcomes. Specifically, in-feed placements experience higher clicks, but due to the annoyance effect, they also experience more bounces relative to in-ad placements. As a result, both in-feed and in-ad placements are similarly effective in generating visits to an advertiser's website. Thus, ad performance between in-feed and in-ad placements is equivocal. However, the costs of generating these visits could differ significantly. While in-feed placements might generate more clicks, they typically cost a price premium and, more importantly, cost-per-click (CPC) bidding models dominate the programmatic advertising space. Consequently, under a CPC model, the advertiser pays for all incremental clicks generated by in-feed placements, limiting the potential for increased profit margins. Moreover, due to the annoyance effect, we found that consumers may punish advertisers when they are redirected from an in-feed placement by reducing their purchase intentions toward the advertising brand.

Taken together, the price premium associated with in-feed ads may not be justified based on current consumer behavior. Our results provide an initial look at the need for further calibration of strategies associated with native ads to improve performance. We encourage managers to strategically examine factors that could impact the efficacy of these ads to justify the increasing cost. In the following sections, we dive deeper and highlight how advertisers can improve their results by better calibrating the bidding process and content given an ad placement.

Improved bidding strategies for advertisers

In the early days of digital display advertising, pricing was fairly similar to that of traditional media. Advertisers paid for the estimated number of impressions of a publisher's website. Then, the cost per click (CPC) model for digital advertising emerged, in which advertisers were able to only pay for users who noticed the ad and clicked on it. More recently, CPC bidding has given way to another model: cost per action (CPA). Under this system, the advertiser pays the publisher only if the user performs an action subsequent to the first click, such as purchasing an item or signing up for a newsletter. Today, advertisers have the option to choose from all three options (Google Display Network, 2023). The challenge for publishers and advertisers alike is determining which pricing model to use.

Recent research by Hu et al. (2016) investigated this issue further – finding that CPC has clear downsides for advertisers. Not only is there the risk of click fraud or the publisher putting little effort into sending the suitable types of consumers to the advertiser's site, but relevant to native advertising, consumers may click on an ad unknowingly, only to click out of it afterward (Hu et al. 2016). In this research context, native advertising could create misalignment between advertisers and publishers. Study 1 found that in-feed placements garnered relatively higher clicks compared to in-ad placements. If we assume that (1) the effects of ad placement hold and (2) the CPC is the same for both in-ad and in-feed placements, publishers clearly benefit while advertisers do not experience any financial benefit. Building on these effects, in Study 2, we find that consumers are more likely to bounce from the advertiser's landing page after clicking on an in-feed placement. With a CPC bidding model, the publisher is already paid and, therefore, bounces do not affect their profitability. However, the advertisers deploying their ads via in-feed placements are left paying for consumers that clicked on the ad, only to leave immediately upon hitting the advertiser's landing page. Moreover, we find in Study 3 that these redirects annoy customers, and in addition to bouncing, they reduce their intentions toward the advertiser, providing multiple downsides for these spurious clicks. At best, it suggests that advertisers are wasting expense on clicks that immediately bounce and, at worst, they are paying to annoy potential customers and reducing future intentions toward their brand.

If these results generalize to the broader native advertising landscape, this has tremendous implications for advertisers. Taking the results of not only this research but other recent work by Aribarg and Schwartz (2020) as well as Wang et al. (2019), publishers are clearly incentivized to sell advertising space in their news feeds. More clicks on in-feed placements not only generate revenue more efficiently in a CPC model, but also give publishers a selling point to advertisers. Without fully understanding the downstream effects of post-click annoyance and bounces, advertisers may sub-optimally bid on in-feed placements.

Calibrated digital marketing campaigns

Once advertisers calibrate the best bidding model for their campaigns, they need to consider ad content and placement strategies. Traditional display ads regularly featured high selling intent ads that would drive consumer action. Since in-feed placements emerged, advertisers are now developing content lower in selling intent with the notion that when they are served in-feed, they will be processed similarly to editorial content (Sharethrough, 2013). Interestingly, we find that in-feed ads get clicked on regardless of selling intent of the ad, so this doesn't appear to matter to consumers. However, when these low selling intent ads are served in-ad, click-through rates dropped significantly. Given the traditional approach to serve high selling intent ads in-ad, this likely shouldn't impact advertisers too much. However, a post-hoc examination of our data from Study 1 revealed that of the 93,677 campaign scenarios served in-ad, over 66% of the ads were of low selling intent (see Table 4). Based on our results of Study 1, this means that two-thirds of the time advertisers were experiencing much lower click-through rates by simply serving in-ad placements with low selling intent ads. Specifically, our results suggest that—holding other factors constant—when high selling intent ads were served in-ad, the expected average click-through rate is 0.018%, a figure that drops to 0.014% when the ads convey low selling intent (see Fig. 2). While that difference may appear insignificant on the surface, there were over 110 million impressions across the 11 ad copies in Study 1, which translates to an incremental gain of over 4,000 clicks.

Consequently, our results suggest the need to calibrate the ad content to placement. This is particularly important for ads served in-ad. However, our data indicate that advertisers are not considering the need for fit between copy and placement and might simply equally split their ad budgets between the two options instead of attempting to optimize the placements to match the content of the ad. For a quick improvement in campaign performance, advertisers can simply match the message to the placement for in-ad placements.

Simulated model of relative performance of in-feed versus in-ad placements with CPC versus CPM bidding

To further examine the implications for digital marketing spend, we simulated the results of several campaigns with one million impressions each (see Web Appendix I). Specifically, the performance (cost per acquisition) of in-ad versus in-feed campaigns across CPC and CPM bidding models—two of the most common display ad bidding strategies (Google Display Network, 2023). To develop these models, we conservatively assumed that in-feed ads would experience a 30% greater click-through rate and 30% higher bounce rate relative to in-ad placements. Given that annoyance is triggered upon redirection to the advertiser's website (Study 3), we assume ad placement is unlikely to influence a consumer's decision to convert after visiting the landing page (i.e., purchase). We then compared the cost of the placements across the two bidding strategies using industry benchmark figures—$1.50 CPC and $1.00 CPM (Wordstream, 2022).

Given these core assumptions coupled with more conservative estimates from the results in Studies 1 and 2, we developed simplified models to calculate the overall cost per acquisition in both CPC and CPM bidding approaches. In the CPC bidding scenario, in-feed performs worse across every financial metric—total cost ($1,307 vs. $1,005), CPM ($1.31 vs. $1.01), cost per visit ($3.13 vs. $2.50), and, most importantly, cost per conversion/action ($34.72 vs. $27.78). This is due to the significantly higher click-through and bounce rates for in-feed ads, suggesting that based on current consumer behavior and pricing models, advertisers should avoid CPC bidding for in-feed placements. However, when looking at the CPM bidding scenario, in-feed placements perform better across all relevant metrics. In this instance, the relatively higher click-through rate passes more consumers to the advertiser's website, so despite a higher bounce rate, the advertiser comes out ahead relative to in-ad placements ($CPA_{\text{in-feed}}$: $26.58, $CPA_{\text{in-ad}}$: $27.64). Granted, this is a hypothetical scenario where publisher, advertiser, and consumer characteristics would undoubtedly influence real-world results, but it provides an interesting thought experiment as to which bidding strategies are optimal for native advertising placements. Consequently, we believe that an interesting avenue for future researchers would be exploring which type of bidding scheme is optimal for in-feed native ads.

Need for evolving advertising services

Collectively our results suggest a need for publishers to evolve their advertising services. Given the high likelihood of bouncing for in-feed native ads due to the annoyance of being redirected off the publisher's site, a change in delivery should be explored. The results of Study 3 demonstrate that simply redirecting consumers off the publisher site from an in-feed placement triggers differentially higher annoyance relative to in-ad placements, which leads to bounce intentions and lower purchase intentions for an advertiser. Without changes to the business model for in-feed ads, these outcomes are not sustainable for advertisers. As a result, we suggest a shift in delivery. Specifically, it seems like the act of being redirected is a trigger that sets the negative downstream consequences in motion. As a result, if publishers can remove this trigger, advertisers could experience better outcomes. For example, we find a significant drop in annoyance for in-feed placement if they are simply directed to a microsite within the publisher's domain that can deliver the same sponsored content developed by the advertiser.

A recent survey of publishers' websites suggests some might be testing these models as US Weekly now hosts content for Walmart rather than redirecting consumers to the Walmart website.[4] Interestingly, this sponsored content page

[4] https://www.usmagazine.com/stylish/pictures/the-top-5-retro-inspired-accessories-you-need-to-elevate-your-home/

on US Weekly has redirects tied to Walmart products and traditional banner ads for Walmart.com. This serving model is very much the exception rather than rule, but it seems to have a lot of promise and we encourage advertisers and publishers to explore more partnership opportunities like this.

Theoretical implications

Given that native advertising is a relatively new form of digital advertising, it is understandable that research on the topic is limited. As a result, this research has important theoretical implications relevant to academics and provides new insight into the drivers of native advertising effectiveness. We discuss these theoretical implications next.

The annoyance effect

Research on native advertising suggests that while initial exposure to native ads may not annoy consumers, they may feel tricked after clicking on them (Wojdynski & Evans, 2016). Wang et al. (2019) initially tested the "annoyance effect" by exploring the effect of rank position of in-feed native ads on click-through rates and conversion rates. We expand upon this theoretical framework on two fronts. First, Wang et al. (2019) focused exclusively on the rank position of in-feed placements. Our research expands upon their work by examining not only in-feed placements, but native ads delivered in the traditional ad space. While other research has compared in-feed placements with traditional banner ads (e.g., Aribarg and Schwartz, 2020), our research provides further insight into the mechanisms that drive clicks. As both types of native ad placements leverage creative elements from the publisher's website, our findings suggest that placement effects are the primary driver of clicks. If the design of native ads alone were the reason for higher click-through rates, we would not have seen a significant main effect for ad placement. Consequently, this provides a unique contribution to the existing literature.

Our second contribution to the literature on the annoyance effect stems from our exploration of post-click performance. Given that consumers may feel tricked after clicking on a native ad (Wojdynski, 2016), one lingering question was at what point would consumers feel tricked? Wang et al. (2019) provide empirical evidence that suggests annoyance is triggered at some point between clicking on the native ad and prior to conversion, but fall short of formally measuring annoyance and, more importantly, identifying how early annoyance is triggered. Our research helps address this gap by examining the transition from an ad click to redirection to the advertiser's landing page. In Study 2, we observe that consumers directed from in-feed placements bounce from the landing page at a higher rate than those directed from in-ad placements—suggesting that annoyance is triggered upon redirection to the advertiser's landing page. This finding is further supported by the results of our follow-up study.

The contingent role of ad content in native advertising

This research also builds upon prior literature calls to assess message appeals' influence on native advertising effectiveness (e.g., Harms et al., 2017). We are the first study to explore how selling intent influences native display advertising effectiveness. Consistent with the digital advertising literature, which has traditionally found positive effects for explicitly promotional content (e.g., Xie et al., 2004), our findings suggest that ads with high selling intent are generally more effective at generating clicks. However, we find a significant interaction between ad placement and the selling intent of the ads, such that the effect of ad placement (i.e., changing from in-ad to in-feed) is significantly stronger for ads with lower levels of selling intent.

Limitations and future research

While this research provides a first step in identifying the advertiser-controlled factors that drive native advertising effectiveness, many questions remain. Given the scope of this research, we only explored the impact of informational content. However, integrative models of advertising suggest that advertising messages can influence consumers through two routes: an informational route and an emotional route. As we did not address the impact of emotional content, we strongly encourage future research to do so. In addition, the effects of in-feed and in-ad placements could be contingent on the number of ads being served within each area on a given publisher's website. While we try to control for domain quality, which could partially account for the prominence of ads versus publisher content, future research should also explore how the prevalence of the various ad types could impact these effects.

One limitation of our research is that the high selling intent ads that were used in Study 1 all offered a financial incentive to buy the advertised product. Conversely, the low selling intent ads offered no such incentives. It would be interesting for future researchers to isolate the incentive effect from the selling intent effect. This is particularly relevant for native advertising as it is increasingly used to promote brands' content marketing initiatives. While we provide some insight into how advertisers can toe this line, we believe that we are merely scratching the surface. Along the same lines, in the second study, we only focused on low selling intent ads given budgetary constraints, but future research could explore similar interplays with ads that were higher in selling intent too.

A second limitation of this research is that we could not control for consumer experience with native advertising. The literature on ad avoidance suggests that previous negative experience with display ads leads to future ad avoidance (Cho & Cheon, 2004). Consequently, it could be possible that as consumers are exposed to more native advertisements, they will be more adept at identifying native ads, particularly in-feed placements. In the long term, this could potentially limit the effectiveness of in-feed placements at generating clicks but could also mitigate the negative post-click behaviors (i.e., because consumers would be understanding of the in-feed ad's intent before clicking, they should be less likely to react negatively to being redirected to the advertiser's landing page).

In summary, the current research provides a first step in understanding what makes native advertising effective. As this new form of digital advertising continues to proliferate, we hope that this article stimulates additional research in this burgeoning field.

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Data Availability The datasets for this research are not publicly available due to confidentiality agreements. However, data are available from the first author upon reasonable request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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