Information Stream Advertising Avoidance Mechanisms and Retargeting Strategies Based on User Dynamic Information Processing

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Date: 2022-09-16T00:00:00+00:00

Abstract

As information stream advertising develops rapidly, user ad avoidance has become increasingly prevalent; however, conclusions from traditional ad avoidance research cannot be directly applied to this context. Based on a dynamic information processing perspective of users, this study seeks to explore (1) the underlying mechanisms of ad blocking and ad skipping behaviors under dynamic information processing states (convergent vs. divergent); (2) employing an attribution-guided retargeting strategy to exploit the signal value derived from the "residual effect" of users' ad blocking; (3) employing an ad salience retargeting strategy to overcome the negative impacts caused by the "learning effect" of users' ad skipping. While enriching existing theories, this study provides theoretical and decision-making support for the responsive optimization of information stream advertising.

Full Text

Preamble

The In-Feed Native Advertising Avoidance Mechanism and Re-Targeting Strategy Based on User Dynamic Information Processing Modes

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Abstract: As in-feed native advertising grows rapidly, user ad avoidance is becoming increasingly prevalent. However, traditional findings on ad avoidance cannot be directly applied to this context. Based on a dynamic information processing perspective, this research seeks to explore (1) the underlying mechanisms of ad-blocking and ad-skipping behaviors under dynamic information processing states (convergent vs. divergent); (2) how to leverage the "residual effect" from ad blocking as a valuable signal through attribution-guided retargeting strategies; and (3) how to overcome the negative impact of the "learning effect" from repeated ad skipping through prominence-based retargeting strategies. While enriching existing theories, this research provides theoretical and managerial guidance for the responsive optimization of in-feed native advertising.

Keywords: in-feed native advertising, dynamic information processing mode, advertising avoidance, advertising retargeting

Classification Number: B849: F713.55

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1. Problem Statement

In-feed native advertising has emerged as a new engine driving the development of online advertising, aligning with mobile information consumption scenarios. According to statistics, in-feed advertising accounted for 36.8% of the market in 2021, ranking second, and is projected to exceed 450 billion RMB in 2022 to become the largest online advertising format (iResearch, 2021). However, behind this apparent prosperity lie hidden concerns: reports indicate that 67% of users have engaged in ad-blocking behaviors on in-feed platforms due to perceived interference with their reading experience (eMarketer, 2020).

Chung and Kim (2021) conducted in-depth interviews with Facebook users aged 19-29 and found that nearly 70% of respondents reported frequently ignoring in-feed ads by quickly skipping them. Ad avoidance behaviors such as blocking and skipping reduce the efficiency of advertisers' marketing expenditures (Chen & Liu, 2022; Dukes et al., 2022) and threaten platform development (Yan et al., 2020). Without sponsorship revenue, platforms cannot sustainably provide high-quality free services, ultimately diminishing overall user welfare (Niu et al., 2021). In stark contrast to the booming industry development, academic research on in-feed advertising remains in its infancy, with limited exploration of in-feed ad avoidance. Unlike traditional media ad avoidance, how and why do users avoid in-feed ads on streaming platforms? How should platforms respond to such avoidance? These are critical issues demanding urgent attention from both industry and academia.

In-feed ad avoidance differs substantially from traditional media ad avoidance across three key dimensions. First, **dynamic vs. stable information processing states**: Traditional media (television, radio, email, newspapers) embed advertisements within relatively fixed contexts, resulting in stable user information processing states (Baek & Morimoto, 2012). In contrast, in-feed ads are embedded within continuously emerging streaming content, where users no longer maintain a single processing state but instead experience dynamic shifts as their browsing context changes (Kanuri et al., 2018). Second, **prominence vs. nativeness**: Traditional ads typically employ prominent formats, with research emphasizing avoidance driven by perceived intrusiveness (Goldfarb & Tucker, 2011). In-feed ads adopt native formats that appear similar to ordinary non-commercial content. Here, perceived interference depends more on the user' s information processing state (Ferreira et al., 2017; Sahni & Nair, 2020). For instance, Ferreira et al. (2017) found that users in goal-directed (vs. non-directed) processing states perceive stronger (or weaker) intrusiveness from in-feed ads. Third, **lagged vs. real-time avoidance responses**: Traditional ad content and placement are relatively fixed, making real-time response to user avoidance difficult and inherently lagged (Baek & Morimoto, 2012). In-feed ad content varies by user and time, enabling platforms to dynamically adjust content and timing based on user feedback (Kanuri et al., 2018). If users remain on the platform after avoiding an ad, platforms theoretically have opportunities for responsive retargeting (Chen & Liu, 2022).

In summary, the dynamic nature of user information processing states, the native characteristics of ad content, and the responsive capability of platforms present new opportunities and challenges for in-feed ad avoidance research. Consequently, traditional ad avoidance findings cannot be directly transferred to in-feed advertising. Research must incorporate platform-specific features, consider how observable browsing behaviors can infer underlying processing states, distinguish the mechanisms of different avoidance behaviors across processing states, and explore how platforms should respond to different avoidance behaviors to improve subsequent ad effectiveness. Building on this logic, this study adopts a dynamic information processing perspective to identify two observable in-feed ad avoidance behaviors—ad blocking and ad skipping—and examine their underlying mechanisms and platform response strategies.

2.1 In-Feed Native Advertising Research

(1) Definition and Characteristics of In-Feed Native Advertising

In-feed native advertising was first introduced by social media giant Facebook in 2006 and has gained increasing popularity among advertisers and platforms with the development of mobile internet. In-feed native advertising refers to internet display ads that align with the characteristics of the host streaming platform, can be responsively adjusted based on real-time user feedback, and possess social functionality attributes (Huang & Zhang, 2019). This emerging ad format revolutionizes the traditional internet display advertising process, transforming three key aspects: ad design, placement, and dissemination.

At the **ad design level**, traditional internet display ads are embedded in webpages with clear boundaries between ads and other content, typically employing highly visible formats to increase user arousal levels and capture attention (Goldfarb & Tucker, 2011). In-feed ads, however, are natively embedded between news items in the user' s reading stream, appearing like ordinary content, with each item entering the user' s visual focus sequentially (Campbell & Evans, 2018). At the **ad placement level**, traditional ads are primarily deployed on one-way publishing PC platforms based on market segmentation, resulting in low personalization and inability to respond to user feedback in real time (Kim et al., 2019). In-feed ads are mainly deployed on decentralized social streaming platforms on mobile devices, with content personalized for each user and capable of dynamic response (Yang & Jiang, 2021). At the **ad dissemination level**, the medium transforms relationships between enterprises and users, and among users themselves. Traditional internet display advertising follows a one-to-many, one-way communication model with limited user interaction (Bell & Buchner, 2018). Mobile social media platforms endow in-feed ads with social functionality, enabling user participation through likes, shares, and comments, thereby connecting users through platform social features (Lee et al., 2018).

(2) Current State of In-Feed Native Advertising Research

Scholars in this field generally focus on two levels: users and advertisements. At the **user level**, current research typically examines precise ad delivery based on stable psychological attributes (e.g., gender, age, social relationships) and historical behavioral attributes (e.g., browsing history). For example, Magesh and Vijayalakshmi (2019) found that optimal ad placement sequences vary by user gender and age. Kim et al. (2016) discovered that high-construal-level ads perform better on weak-tie public information pages, while low-construal-level ads excel on strong-tie personal pages. At the **ad level**, research explores how to enhance effectiveness through ad format and content. Aribarg and Schwartz (2020) found that moderate brand prominence in in-feed ads better balances persuasion, brand recognition, and platform trust. Wojdynski and Evans (2016) argued that placing ads in middle or bottom positions with "ad" or "sponsored" labels in corners attracts attention while also triggering perceptions of persuasive intent.

While existing literature offers rich insights from various perspectives, two limitations are notable. First, in antecedent research, studies focus on relatively static, stable, and historical user attributes, neglecting the dynamic and responsive characteristics of streaming platforms and overlooking the impact of dynamic changes in information processing during browsing. Second, in outcome research, studies emphasize positive effects like clicks, shares, and purchase intentions, paying insufficient attention to negative outcomes such as ad blocking and skipping.

2.2 Information Processing State Research

(1) Definition and Typology of Information Processing States

Information processing theory posits that human cognition is a process of information processing, where processing states influence how individuals process information, processing speed, cognitive states, and ultimately decision-making (Hong & Desai, 2020; Thompson & Hamilton, 2006). The concept of information processing mode has two dimensions: at the behavioral level, it refers to information processing methods when facing information tasks; at the psychological level, it refers to the cognitive state during information processing (Huang et al., 2009; Thompson & Hamilton, 2006). Scholars typically adopt a dichotomy to classify individual information processing states from different perspectives. For example, Dickinger and Stangl (2011) divided online information search into goal-directed and experiential search based on whether users have clear objectives. Rezaei et al. (2016) categorized web browsing into utilitarian and hedonic types based on user motivation. Ruiz and Sicilia (2004) distinguished between cognitive and affective processing styles based on users' thinking modes. Despite varied classifications, they generally stem from two attributes: behavioral orientation and cognitive state during information processing.

(2) Information Processing States in In-Feed Advertising

Extensive advertising research has examined how information processing states influence traditional ad cognition and decision-making (Hossain, 2018; Siefert et al., 2008; Zhang et al., 2014). For instance, Thompson and Hamilton (2006) found that consumers in analytical processing states prefer comparative ads, while those in imagery processing states prefer non-comparative ads. Jung et al. (2014) showed that consumers in telic (goal-directed) modes respond more positively to low-interactivity web ads, while those in paratelic (non-directed) modes prefer high-interactivity ads.

Current research primarily examines static information processing perspectives on individual ads because traditional ad contexts are relatively fixed. In-feed advertising contexts differ in two ways: (1) **Dynamic ad placement positions**—In-feed ads appear after several news items, with placement varying by user and time (Wang et al., 2019). (2) **Dynamic user information selection**—Users freely and autonomously choose content, sometimes reading similar topics in depth, other times diversifying across topics. Reversal theory suggests that individual cognition is complex and variable, heavily influenced by context (Semaan et al., 2019). The dynamic nature of both objective placement and subjective information selection in in-feed ad contexts triggers dynamic shifts in users' information processing states. While search ads share similarities with in-feed ads in appearing sequentially within streams, search ads are user-initiated and contextually consistent with search keywords. In-feed ads are algorithmically placed with diverse, generally unrelated content, making users more susceptible to different processing states (Zhou & Xue, 2019).

2.3 Advertising Avoidance Research

(1) Types, Antecedents, and Consequences of Traditional Advertising Avoidance

Advertising avoidance has long been considered one of advertisers' greatest obstacles. As Speck and Elliott (1997) noted, "Any form of ad avoidance reduces ad content exposure and weakens ad effectiveness." Advertising avoidance encompasses user responses across three levels: cognition, affect, and behavior (Cho & Cheon, 2004). **Cognitive avoidance** refers to negative cognitions leading users to actively ignore ads ("I don't believe it"). **Affective avoidance** involves negative emotions and attitudes ("I don't like it"). **Behavioral avoidance** includes actions like fast-forwarding, changing channels, closing windows, or averting gaze ("I won't watch it").

Previous research has extensively examined antecedents and consequences of ad avoidance across traditional media (magazines, newspapers, radio, TV, email, SMS, banner ads) (Baek & Morimoto, 2012; Bang et al., 2018; Michelon et al., 2020; Speck & Elliott, 1997). Antecedent research primarily focuses on three levels: ad characteristics, user traits, and media vehicles (Cho & Cheon, 2004; Seyedghorban et al., 2016; Teixeira et al., 2010). Due to traditional media's top-down vertical communication nature, scholars generally view ad intrusiveness as the primary cause of avoidance. Outcome research predominantly examines negative effects on advertisers, platforms, and consumers (Teixeira et al., 2010; Yan et al., 2020). Nevertheless, some scholars adopt a positive perspective, exploring how ads can generate effects despite avoidance. For example, Brasel and Gips (2008) found through eye-tracking that brand information in TV ad center regions receives more attention during fast-forwarding than normal viewing. Bellman et al. (2010) examined the residual effect of ad avoidance, comparing five avoidance forms against full ad exposure and finding that partial exposure still yields positive effects on ad cognition, attitude, and recall.

(2) In-Feed Native Advertising Avoidance Mechanisms

Recent research has extended ad avoidance to in-feed advertising. Current models mostly extend traditional ad avoidance frameworks, focusing on antecedents to reduce avoidance. For instance, Niu et al. (2021) applied psychological ownership theory, arguing that in-feed ads in social media cause avoidance by invading users' attention and personal space. Chung and Kim (2021) used social influence theory, suggesting brand reputation and fan count affect avoidance beyond intrusiveness. Chinchanachokchai and De Gregorio (2020) examined consumer socialization, finding avoidance is influenced by susceptibility to peers and social media. Youn and Kim (2019) applied psychological reactance theory, identifying perceived invasiveness and freedom threat as primary avoidance drivers. Despite varied perspectives, scholars increasingly emphasize contextual features because in-feed media users have greater autonomy with fragmented behaviors and contextualized decisions (Martins et al., 2019), making situational features increasingly important for ad effectiveness (Yang & Jiang, 2021). This study incorporates users' information processing states as a key situational feature to examine in-feed ad avoidance under dynamic processing conditions.

(3) Blocking and Skipping in In-Feed Advertising

In-feed advertising exhibits two observable avoidance behaviors: ad blocking and ad skipping (Chen & Liu, 2022; Chung & Kim, 2021; Dukes et al., 2022). **Ad blocking** refers to users clicking the close button to block an ad—a clearly observable behavior directly recorded by servers. Most platforms currently optimize subsequent ad delivery based on blocking data (Chen & Liu, 2022; Niu et al., 2021). Streaming platforms exhibit two types of "skipping" behaviors: (a) neutral information selection where users scroll past ads without any action (not considered avoidance) (Bellman et al., 2010), and (b) active ad skipping where users deliberately ignore ads by quickly scrolling past them—an avoidance behavior analogous to fast-forwarding video ads (Dukes et al., 2022). These two skipping types can be distinguished by analyzing the distribution of ad reading duration and timestamps between information items. If skipping speed matches average speed for regular content, it' s normal selection; if significantly faster, it' s ad avoidance (Belanche et al., 2017; Dukes et al., 2022).

Current ad avoidance research has not separately examined the mechanisms underlying different avoidance behaviors. However, in streaming media contexts, ad blocking and skipping differ fundamentally: First, blocking indicates users noticed the ad, while skipping indicates they ignored it. Second, blocking requires substantial behavioral and cognitive effort compared to skipping (Chen & Liu, 2022), whereas skipping means users identified but didn' t process the ad before scrolling past (Dukes et al., 2022). Third, blocking signals psychological reactance (Niu et al., 2021), while skipping evokes minimal psychological response (Belanche et al., 2017). These substantial differences necessitate separate investigation to illuminate the black box of in-feed ad avoidance.

2.4 Advertising Retargeting Research

Big data-empowered enterprises can identify more precise user preferences after ad delivery failures to conduct retargeting (Villas-Boas & Yao, 2021). Traditional ad retargeting research has focused on two aspects: (1) **Impact of retargeting on ad effectiveness**. For example, Villas-Boas and Yao (2021) found positive effects of retargeting based on search behavior in search advertising contexts. Sahni and Nair (2020) showed that retargeting banner ads brought 14.6% of consumers back to websites within four weeks. (2) **Timing effects of retargeting**. Li et al. (2021) emphasized the importance of timeliness in SMS and email retargeting, arguing that "striking while the iron is hot" yields better results. Bleier and Eisenbeiss (2015) noted that retargeting based on browsing history produces positive effects that decay over time.

Existing literature predominantly focuses on retargeting based on positive signals like browsing, searching, and cart additions. However, research on retargeting based on negative signals like ad avoidance remains unexplored. This study examines retargeting after in-feed ad avoidance for two reasons: First, streaming platforms can capture avoidance behaviors (Kanuri et al., 2018), providing insights for retargeting. Second, platforms can respond to user feedback in real time (Chen & Liu, 2022), enabling responsive retargeting opportunities.

2.5 Literature Review Summary

The aforementioned literature provides a solid foundation. However, regarding in-feed ad blocking and skipping, current research exhibits three gaps that this study addresses:

First, **limited research on in-feed ad avoidance**. Current in-feed ad research focuses on positive responses like clicks, purchase intentions, and shares (Kim et al., 2017; Yang & Jiang, 2021; Zhou & Xue, 2019), with minimal exploration of negative responses like avoidance (Chung & Kim, 2021). Studying in-feed ad avoidance is theoretically significant and practically valuable for comprehensively understanding ad effectiveness.

Second, **insufficient attention to dynamic information processing impacts on user cognition and preferences**. Information processing research typically adopts static perspectives on differences across processing states (Siefert et al., 2008; Thompson & Hamilton, 2006; Zhang et al., 2014). However, in the mobile internet era, users exhibit fragmented, contextualized, and mobile decision-making behaviors (Huang & Zhang, 2019), with processing states dynamically shifting across contexts. This study explores the relationship between dynamic information processing states and in-feed ad avoidance, enriching information processing theory' s application in the mobile internet context.

Finally, **lack of research on post-avoidance retargeting**. Current ad avoidance research focuses on antecedents to reduce avoidance (Youn & Kim, 2019), remaining at the problem-identification stage rather than solution development. The responsive nature of streaming platforms provides opportunities to explore post-avoidance retargeting. This study constructs a relatively complete in-feed ad avoidance model that highlights the signal value of avoidance behaviors to guide retargeting and overcome negative effects on subsequent ad effectiveness.

3. Research Framework

This study aims to deepen theoretical understanding of in-feed ad avoidance mechanisms from a dynamic information processing perspective while helping platforms responsively optimize retargeting strategies. Specifically, it pursues three objectives: (1) Explain why and how users avoid in-feed ads under dynamic processing states—identifying factors causing blocking vs. skipping and their mechanisms, and modeling the dynamic avoidance decision process; (2) Examine platform retargeting strategies after ad blocking—since blocking is easily observable, what impact does it have on subsequent ads, and how can the "residual effect" from blocking be leveraged for retargeting? (3) Investigate retargeting after ad skipping—since skipping yields minimal ad exposure and platforms struggle to extract signals from such "turning a blind eye" behavior, how can platforms interrupt this pattern when high-frequency skipping occurs? Research shows that capturing user attention is key to breaking skipping patterns (Brasel & Gips, 2008; Siefert et al., 2008). This study explores how "prominence strategies" can interrupt skipping behavior. The theoretical framework is illustrated in Figure 1 [Figure 1: see original paper].

Study 1: Mechanisms of In-Feed Ad Avoidance Based on Dynamic Information Processing States
Study 2: Platform Retargeting Strategies After Ad Blocking
- Ad Blocking → Attribution-Guided Strategy → Subsequent Ad Effectiveness
- Information Processing State (Convergent vs. Divergent) → Ad Element Intrusiveness (Concrete vs. Abstract) → Ad Blocking/Skipping → Subsequent Ad Effectiveness
- Ad Skipping → Prominence Strategy → Subsequent Ad Effectiveness

Study 3: Platform Retargeting Strategies After Ad Skipping
Figure 1 illustrates this research framework.

3.1 Study 1: Mechanisms of In-Feed Ad Avoidance Based on Dynamic Information Processing States

(1) Study 1a: Mechanisms of In-Feed Ad Blocking and Skipping

As discussed, streaming platforms exhibit two observable avoidance behaviors: ad blocking and ad skipping. Since platform information is presented in a top-down, continuous, sequential format—showing several news items followed by an ad (Wang et al., 2019)—users' content selection and processing methods differ before encountering different ads. Advertising research demonstrates that ad context or preceding information affects ad cognition and decision-making (Kim & Meyers-Levy, 2008; Zhang et al., 2014; Fan et al., 2018). However, previous studies examined static contexts with single background information, leaving unexplored the effects of series of information items in dynamic streaming contexts. In streaming platforms, users' cognitive states dynamically shift across browsing contexts (Siefert et al., 2008; Zhang et al., 2014). This study examines the mechanisms underlying these two distinct avoidance decisions from a dynamic information processing perspective.

Based on user browsing patterns, dynamic browsing can be classified as **convergent** or **divergent**. **Convergent** browsing involves deep exploration of information within a specific domain, with selected items showing high thematic similarity (Björneborn, 2008; Nejati & Balasubramanian, 2016). **Divergent** browsing involves broad exploration across diverse information, with selected items covering different themes or substantially different content (Björneborn, 2008; Huang et al., 2009). Since information selection is autonomous and free, users' processing states dynamically transform as browsing patterns change (Hong & Desai, 2020; Zhang et al., 2014).

Psychological reactance theory posits that when users perceive media as their personal space, ads threatening their autonomy trigger resistant behaviors like blocking to restore autonomy (Bang et al., 2018; Youn & Kim, 2019). Convergent processing is typically goal-directed, aiming to reinforce information in a domain, creating high autonomy needs and low tolerance for interruption (Oliveira-Castro & Foxall, 2017; Youn & Kim, 2019). Niu et al. (2021) found that users with clear browsing goals more easily perceive ad interference with psychological ownership, including both attention and spatial invasiveness, prompting ad blocking. Visual cognition research shows uneven attention allocation to different ad elements across processing states (Monga & John, 2008; Thompson & Hamilton, 2006). In convergent, analytical processing states, users focus more on concrete elements facilitating rational judgment—such as product type, function, and price—precise, specific information with physical references (Dewi & Ang, 2020; Hur et al., 2020). Thus, we infer that in convergent states, concrete element intrusiveness more likely threatens autonomy, triggering ad blocking.

Cognitive resource theory suggests that users have limited cognitive resources, with ads competing against other information for attention. Ads failing to generate psychological arousal are ignored and quickly skipped (Dukes et al., 2022; Romberg et al., 2020). In divergent processing states, users seek stimulation, arousal, and boredom prevention (Björneborn, 2008). For example, Kwon and Jain (2009) found that users seek optimal arousal levels through diversified information. Divergent processing is associated with hedonic motivation and feeling-based, non-purposeful, low-effort, fast decision-making, triggering holistic abstract thinking (Dickinger & Stangl, 2011; Kwon & Jain, 2009; Sharma et al., 2010). Here, users more easily attend to abstract elements requiring less cognitive effort but generating attention arousal—such as brand, images, colors, and layout (Bang & Wojdynski, 2016; Dewi & Ang, 2020). In divergent states, only high-arousal information stands out (Björneborn, 2008); if abstract elements fail to generate arousal, ads are easily skipped. Therefore, this study proposes:

Proposition 1: In convergent information processing states, users are more susceptible to concrete element intrusiveness in in-feed ads, which threatens autonomy and leads to ad blocking.

Proposition 2: In divergent information processing states, the inability of abstract elements to generate high arousal leads users to skip in-feed ads.

(2) Study 1b: Dynamic Decision Model of In-Feed Ad Avoidance

The above mechanisms statically explain blocking and skipping but cannot adequately capture how users generate coherent, interrelated ad decisions across different processing states. Since user decisions on streaming platforms are typically continuous and sequential, isolating individual decisions ignores interdependencies, causing biased and inconsistent model estimates. Therefore, a holistic dynamic model is needed to fit the ad avoidance process. Markov random walk processes have been important for modeling dynamic processes across contexts (Liu et al., 2021; Zhuang et al., 2021). Recently, Markov-derived models like hidden Markov models (Liberali & Ferecatu, 2022) and multi-state hazard models (Yu, 2021) have been widely applied to model consumer decision dynamics. This study' s modeling of dynamic ad decisions builds on classic literature

(Le-Rademacher et al., 2018), adjusting model specifications (e.g., time discreteness, random effect distributions) and core parameters (e.g., state transition matrices, factors influencing avoidance) based on streaming platform realities and previously hypothesized mechanisms. Ultimately, a **multi-state frailty model** is constructed to capture the dynamic avoidance process. This model relaxes the time-homogeneity assumption of classic Markov models (Zhuang et al., 2021), considering cumulative effects where all ads seen during a browsing session may influence subsequent ad responses. The frailty model also accounts for user heterogeneity and unobserved latent variables beyond traditional hazard models (Tran et al., 2020).

Specifically, the model defines: **State 1** as the initial browsing state, **State 4** as the final absorbing state when browsing ends at time *t*. The model focuses on ad-related decisions between these states: **ad skipping (State 2)** and **ad blocking (State 3)**. While clicks, shares, and comments may occur, they are not this study' s focus; the model simplifies by including only avoidance states, as shown in Figure 2 [Figure 2: see original paper].

In Figure 2, when users begin browsing (State 1), risks accumulate for transitions to States 2, 3, or 4—potentially skipping (a1: 1\$→2), $blocking(a2 : 1 \to 3), orendingbrowsingwithoutavoidance(a3 : 1 \to 4). AftertransitioningtoState2, risksaccumulateforreturn$ $2 \to 1), furtherblocking(b2 : 2 \to 3), orending(b3 : 2 \to$ \$4). Similar transitions apply from State 3. State 4 is an **absorbing state**—once entered, the dynamic process terminates. Transitions sharing the same origin or destination exhibit within-sample correlation requiring control.

The model defines random variable T as the time of state transition, recorded in milliseconds. The hazard rate for transitioning from state m to n at time t is the conditional probability:

$$\lambda_{m \to n}(t) = \lim_{\Delta t \to 0} \frac{P(t \le T < t + \Delta t \mid T \ge t)}{\Delta t}$$

This hazard rate can be decomposed into baseline hazard (non-parametric) and factor-driven hazard (parametric), yielding a semi-parametric model:

$$\lambda_{m \to n}(t \mid Z(t)) = \lambda_0(t) \exp(\beta_{m \to n}^T Z(t))$$

where *Z(t)* represents factors influencing ad skipping/blocking from previous hypotheses, and β are corresponding coefficients. *X(t) = {Z(s) / 0 ≤ s ≤ t}* captures information processing states (convergent/divergent) up to time *t*. To control for unobserved heterogeneity (e.g., individual content and ad response preferences), a frailty term is added:

$$\lambda_{m \to n}(t \mid Z(t), v) = \lambda_{0,m \to n}(t) \exp(\beta_{m \to n}^T Z(t) + v)$$

where random variable v controls unobserved individual heterogeneity, typically assumed to follow a gamma distribution with mean 1 and variance (Aboulnasr et al., 2008). Parameters can be estimated using penalized maximum likelihood in R' s frailtypack.

In summary, this dynamic model focuses on the dynamic process of ad decisions, moving beyond static examination of individual decisions to provide continuous, dynamic insights while testing whether the proposed blocking and skipping mechanisms hold under dynamic conditions.

3.2 Study 2: Platform Retargeting Strategies After Ad Blocking

While Study 1 examined blocking mechanisms, platforms are more concerned with responses after blocking. Most scholars have focused on blocking' s negative impacts (Baek & Morimoto, 2012; Cho & Cheon, 2004). However, are all blocking effects negative? Research shows avoidance creates residual effects—cognitive memory of ads (Bellman et al., 2010; Brasel & Gips, 2008). Bellman et al. (2010) compared four TV ad avoidance types, finding that greater cognitive and behavioral effort during avoidance yields stronger residual effects. The mere exposure effect suggests that familiarity with previous experiences is preferred over new stimuli, making familiar ads process more fluently than novel ones (Fang et al., 2007; Montoya et al., 2017). Since preference judgments are rapid and non-deliberative, increased fluency enhances preference for familiar ads (Bell & Buchner, 2018). How can platforms leverage residual effects to improve subsequent ads?

Based on the classic misattribution model (Bornstein & D' agostino, 1992), whether residual effects from blocking yield positive outcomes depends on whether users perceive fluency in subsequent ad processing without attributing it to previous exposure (Bell & Buchner, 2018). Major platforms are experimenting with different blocking attribution strategies. For example, Baidu offers both abstract attributions (e.g., "not interested") and concrete ones (e.g., "block this brand"). Toutiao similarly provides abstract (e.g., "block this ad category") and concrete (e.g., "block this brand") options. Do different attribution strategies affect subsequent ad attitudes? How?

Research shows that activating abstract thinking induces holistic thinking modes (Monga & John, 2008), where users view ads as wholes and attribute blocking to overall dislike. Activating concrete thinking induces analytical modes (Yoon, 2013), where users see ad elements as independent and attribute blocking to specific elements. Thus, concrete attribution strategies encourage users to attribute blocking to specific elements rather than the entire ad. When users select abstract blocking reasons, it indicates overall ad dislike, creating negative residual effects. When selecting concrete reasons like "block this brand," it signals negative brand cognition while other elements (e.g., product category) may retain residual effects, increasing fluency for same-category, different-brand ads and improving attitudes. Therefore:

Proposition 3: Concrete (vs. abstract) blocking attributions positively influence subsequent ad attitudes toward same-category (vs. different-category) products.

As noted in Study 1, convergent processing focuses on concrete elements (Dewi & Ang, 2020), while divergent processing focuses on abstract elements (Kwon & Jain, 2009). If users continue browsing after blocking, convergent processing of concretely-attributed ads enhances attention to concrete elements, strengthening positive residual effects. Divergent processing reduces attention to concrete elements, decreasing familiarity and weakening positive residual effects. Thus:

Proposition 4: Convergent (vs. divergent) information processing states enhance the positive effect of concrete blocking attributions on subsequent same-category product ad attitudes.

After determining post-blocking ad strategies, when should platforms deliver subsequent ads for optimal effect? Research shows that ads delivered too soon after being perceived as intrusive are more likely to be seen as disruptive (Wang et al., 2019). Therefore, after blocking, platforms should not immediately deliver ads but allow users to read non-commercial content to restore autonomy. However, delivery should not be too delayed, as retargeting effectiveness is time-sensitive (Li et al., 2021) and residual effects decay over time (Bellman et al., 2010). Thus:

Proposition 5: The positive effect of concrete blocking attributions on subsequent same-category product ad attitudes follows an inverted U-shaped relationship with the time interval between the blocked ad and subsequent ad.

3.3 Study 3: Platform Retargeting Strategies After Ad Skipping

Compared to blocking, ad skipping is more prevalent yet under-examined. While blocking generates ad exposure and cognitive residue for retargeting, skipping involves active ad ignorance with minimal exposure (Cho & Cheon, 2004), making it difficult for platforms to extract retargeting signals. Moreover, research shows that users experiencing "learning effects" during continuous information processing become increasingly likely and faster to skip subsequent ads (Belanche et al., 2017). High-frequency skipping creates continuous, habitual skipping patterns that significantly damage platform ad revenue (Dukes et al., 2022). How can platforms intervene when ad skipping occurs?

Visual marketing and perceptual psychology research indicates that capturing user attention is key to breaking skipping patterns (Brasel & Gips, 2008; Siefert et al., 2008). When skipping frequency is high, platforms must adjust strategies to evoke higher attention and prevent subsequent skipping. However, the native characteristics of in-feed ads challenge attention capture. Aribarg and Schwartz (2020) found that nativity meets users' experiential needs but risks reducing arousal and attention, potentially weakening effectiveness. Research shows in-feed ads should not be overly native; appropriate prominence is needed to capture attention and achieve persuasion (Campbell & Evans, 2018; Wojdynski & Evans, 2020). Two paths enhance prominence: (1) increasing concrete element prominence through sponsor clarity, disclosure, and deception avoidance (Wojdynski et al., 2017); (2) increasing abstract element prominence through brand salience (Aribarg & Schwartz, 2020).

Attention engagement theory suggests that information processing states differentially affect attention selection and engagement with ad elements (Pieters & Wedel, 2004). In convergent states, detailed concrete thinking is activated, leading to careful step-by-step analysis and greater attention to concrete elements (Dewi & Ang, 2020). In divergent states, users focus more on abstract elements requiring less deep cognitive processing (Dickinger & Stangl, 2011). Therefore:

Proposition 6: When users exhibit in-feed ad skipping, information processing states moderate the effect of subsequent ad prominence strategies on attention. Specifically: In convergent processing states, subsequent ads using concrete element prominence strategies positively affect attention; in divergent states, ads using abstract element prominence strategies positively affect attention.

3.4 Research Methodology

This study employs multiple methods for cross-validation: in-depth interviews, modeling with real platform data, laboratory experiments, and field experiments. Specifically: First, based on literature review, conduct interviews with consumers, advertising professionals, and platform ad department staff to explore ad delivery mechanisms, reasons for blocking/skipping, and platform responses to refine the theoretical model. Second, partner with representative streaming platforms to obtain de-identified ad impression data. Following Netzer et al.' s (2008) hidden Markov framework, observable browsing content and ad feedback (clicks, dwell time) can infer unobservable dynamic processing states. Use multi-state hazard models (Yu, 2021) to model how dynamic processing states and ad element characteristics affect avoidance. Third, to validate avoidance mechanisms, conduct a 2 (processing state: convergent vs. divergent) between-subjects experiment using eye-tracking to record fixation counts and durations. Then build a virtual streaming platform for a 2 (processing state) × 2 (element intrusiveness: concrete vs. abstract) design, using real news materials to manipulate processing states and record avoidance, click, and attention data. This design better captures realistic platform responses with reduced external interference. Finally, conduct field experiments using difference-in-differences to evaluate retargeting effectiveness after ad blocking.

4. Theoretical Contributions and Innovations

In-feed advertising is developing rapidly while ad avoidance becomes increasingly prominent. Although recent studies have begun exploring in-feed ad avoidance (Chung & Kim, 2021; Niu et al., 2021), they rely on extensions of traditional ad avoidance models without considering in-feed characteristics. Unlike traditional media, streaming platforms emphasize user orientation, granting users more decision autonomy and making ad avoidance inevitable. The dynamic, native, and responsive nature of streaming platforms (Huang & Zhang, 2019) renders traditional ad avoidance conclusions inapplicable. Unlike traditional ads with relatively fixed contexts, in-feed ad contexts change dynamically (Kanuri et al., 2018), and users' information processing states shift across browsing contexts (Björneborn, 2008; Fan et al., 2018). This study breaks through the limitation of focusing only on static user attributes, examining dynamic processing states to identify blocking and skipping behaviors and explore their mechanisms and retargeting strategies.

First, this study establishes a dynamic information processing-based mechanism for in-feed ad avoidance. Blocking and skipping are common and observable avoidance behaviors, yet existing research has not separately examined their antecedents and mechanisms, ignoring their fundamental differences (Chen & Liu, 2022; Chung & Kim, 2021; Dukes et al., 2022). Moreover, limited in-feed avoidance research extends traditional models with insufficient consideration of streaming platforms' dynamic features (Campbell & Evans, 2018; Lee et al., 2018). This study identifies blocking and skipping behaviors, classifies processing states as convergent or divergent based on browsing patterns, and explores their distinct mechanisms. Psychological reactance theory suggests that ads threatening autonomy trigger blocking to restore autonomy (Bang et al., 2018; Youn & Kim, 2019). In convergent states with high autonomy needs, concrete elements are more salient, leading to blocking driven by concrete element intrusiveness. Cognitive resource theory suggests limited cognitive resources cause ads lacking arousal to be skipped (Dix et al., 2010; Dewi & Ang, 2020). In divergent states requiring high arousal, abstract elements are more salient, leading to skipping when abstract elements fail to generate sufficient arousal. The multi-state frailty model captures this dynamic process, providing continuous insights beyond static mechanism examination.

Second, this study proposes retargeting strategies after ad blocking. While previous research focused on blocking' s negative impacts and how to reduce them (Chen & Liu, 2022; Niu et al., 2021), this study transforms avoidance into valuable signals for retargeting. Research shows blocking' s cognitive and behavioral effort creates residual effects enhancing ad memory (Bellman et al., 2010; Brasel & Gips, 2008). Whether these effects are positive depends on users perceiving fluency without attributing it to previous exposure (Bell & Buchner, 2018). Platforms' blocking attribution options (concrete vs. abstract) activate different thinking modes: concrete attributions induce analytical thinking, attributing blocking to specific elements, while abstract attributions induce holistic thinking, attributing blocking to overall dislike. Thus, concrete (vs. abstract) attributions positively affect subsequent same-category (vs. different-category) product attitudes. The study further examines moderating effects of processing states and ad insertion timing, proposing that convergent (vs. divergent) states enhance the positive effect of concrete attributions on same-category attitudes, and that this effect follows an inverted U-shape with time intervals.

Finally, this study proposes retargeting strategies after ad skipping. Compared to blocking, skipping is more convenient for users, yields less ad exposure, and once habitualized, substantially reduces ad effectiveness (Dukes et al., 2022). Research has not sufficiently distinguished skipping from other avoidance behaviors (Belanche et al., 2017) nor addressed how to retarget when high-frequency skipping occurs (Dukes et al., 2022). Learning effects increase skipping likelihood (Belanche et al., 2017), while capturing attention is key to breaking this pattern (Brasel & Gips, 2008; Siefert et al., 2017). Attention engagement theory suggests processing states differentially affect attention to ad elements (Pieters et al., 2007). In convergent states, concrete thinking increases attention to concrete elements, suggesting concrete prominence strategies enhance attention. In divergent states, abstract thinking increases attention to abstract elements, suggesting abstract prominence strategies enhance attention.

This study' s theoretical contributions are threefold: First, it extends in-feed ad avoidance research. Current literature focuses on improving precision marketing effectiveness (Kanuri et al., 2018; Wojdynski et al., 2017), yet platforms exhibit both observable blocking and less observable skipping behaviors. The lack of differentiated examination of these distinct avoidance behaviors widens the research-practice gap. This study provides a more granular exploration of blocking and skipping mechanisms from a dynamic processing perspective, opening the black box of in-feed ad avoidance.

Second, it enriches information processing theory perspectives. Most applications adopt static perspectives on processing state differences (Wojdynski et al., 2017; Youn & Kim, 2019). However, mobile internet users exhibit fragmented, contextualized, mobile behaviors with dynamically shifting processing states (Huang & Zhang, 2019). This study distinguishes convergent and divergent processing states based on browsing patterns, clarifying user differences across states and exploring dynamic relationships between processing states and ad avoidance, deepening theoretical application in the mobile era.

Finally, it advances post-avoidance retargeting research. While antecedent research is rich (Youn & Kim, 2019), it remains at the problem-identification stage without addressing solutions. Streaming platforms' responsiveness provides an ideal context for post-avoidance retargeting. This study constructs a relatively complete in-feed ad avoidance model highlighting avoidance signals as retargeting guidance to overcome negative effects, expanding the scope of ad avoidance research.

The expected findings also have important practical implications. For advertisers, understanding avoidance psychology improves ad efficiency and reduces wasted marketing spend. For platforms, dynamic processing perspectives enable more granular, real-time, precise user need characterization, improving user experience, reducing churn, building stable user relationships, and enhancing advertiser trust for sustainable development. For users, this means better-targeted ads that match browsing states rather than causing interference, enabling continued enjoyment of free, high-quality information services and improved overall welfare.

References

[1] iResearch. (2021). *2021 China Online Advertising Annual Insights Report - Industry Edition*. Retrieved September 14, 2021, from https://www.iresearch.com.cn/Detail/report?id=3844&isfree=0
[2] Fan, S., Lu, Y., & Hu, Y. (2018). The impact of consistency and sociality on in-feed ad avoidance in social media contexts. *Journal of Management*, 15(5), 759–766.
[3] Huang, M., & Zhang, H. (2019). Frontier practices and theoretical explanations of in-feed native advertising. *Economic Management*, 41(04), 193–208.
[4] Yan, L., Mei, S., & Zhong, W. (2020). The impact of consumer ad-blocking behavior on media platform competition and social welfare. *Journal of Industrial Engineering and Engineering Management*, 34(01), 17–24.
[5] Aboulnasr, K., Narasimhan, O., Blair, E., & Chandy, R. (2008). Competitive response to radical product innovations. *Journal of Marketing*, 72(3), 94–110.
[6] Aribarg, A., & Schwartz, E. M. (2020). Native advertising in online news: Trade-offs among clicks, brand recognition, and website trustworthiness. *Journal of Marketing Research*, 57(1), 20–34.
[7] Baek, T. H., & Morimoto, M. (2012). Stay away from me. *Journal of Advertising*, 41(1), 59–76.
[8] Bang, H., Kim, J., & Choi, D. (2018). Exploring the effects of ad-task relevance and ad salience on ad avoidance: The moderating role of internet use motivation. *Computers in Human Behavior*, 89(7), 70–78.
[9] Belanche, D., Flavián, C., & Pérez-Rueda, A. (2017). Understanding interactive online advertising: Congruence and product involvement in highly and lowly arousing, skippable video ads. *Journal of Interactive Marketing*, 37(1), 75–88.
[10] Bell, R., & Buchner, A. (2018). Positive effects of disruptive advertising on consumer preferences. *Journal of Interactive Marketing*, 41(1), 1–13.
[11] Bellman, S., Schweda, A., & Varan, D. (2010). The residual impact of avoided television advertising. *Journal of Advertising*, 39(1), 67–82.
[12] Björneborn, L. (2008). Serendipity dimensions and users' information behaviour in the physical library interface. *Information Research*, 13(4), 13–14.
[13] Bleier, A., & Eisenbeiss, M. (2015). Personalized online advertising effectiveness: The interplay of what, when, and where. *Marketing Science*, 34(5), 669–688.
[14] Bornstein, R. F., & D' agostino, P. R. (1992). Stimulus recognition and the mere exposure effect. *Journal of Personality and Social Psychology*, 63(4), 545–552.
[15] Brasel, S. A., & Gips, J. (2008). Breaking through fast-forwarding: Brand information and visual attention. *Journal of Marketing*, 72(6), 31–48.
[16] Campbell, C., & Evans, N. J. (2018). The role of a companion banner and sponsorship transparency in recognizing and evaluating article-style native

advertising. *Journal of Interactive Marketing*, 43(2), 17–32.
[17] Chen, Y., & Liu, Q. (2022). Signaling through advertising when an ad can be blocked. *Marketing Science*, 41(1), 166–187.
[18] Chinchanachokchai, S., & De Gregorio, F. (2020). A consumer socialization approach to understanding advertising avoidance on social media. *Journal of Business Research*, 110(1), 474–483.
[19] Cho, C. H., & Cheon, H. J. (2004). Why do people avoid advertising on the internet? *Journal of Advertising*, 33(4), 89–97.
[20] Chung, Y. J., & Kim, E. (2021). Predicting consumer avoidance of native advertising on social networking sites: A survey of facebook users. *Journal of Promotion Management*, 27(1), 1–26.
[21] Dewi, I. J., & Ang, S. H. (2020). Assessing the imagination scale' s nomological validity: Effect of hedonic versus utilitarian product types and abstract versus concrete advertising execution. *Gadjah Mada International Journal of Business*, 22(2), 118–136.
[22] Dickinger, A., & Stangl, B. (2011). Online information search: Differences between goal-directed and experiential search. *Information Technology & Tourism*, 13(3), 239–257.
[23] Dukes, A., Liu, Q., & Shuai, J. (2022). Skippable ads: Interactive advertising on digital media platforms. *Marketing Science*, 41(3), 528–547.
[24] eMarketer. (2020). *Attitude toward social media advertising according to adults in Australia*. Retrieved July 20, 2020, from https://www.emarketer.com/chart/240480/attitudes-toward-social-media-advertising-according-adults-australia-by-gender-jan-2020-of-respondents-each-group.
[25] Fang, X., Singh, S., & Ahluwalia, R. (2007). An examination of different explanations for the mere exposure effect. *Journal of Consumer Research*, 34(1), 97–103.
[26] Ferreira, C., Michaelidou, N., Moraes, C., & McGrath, M. (2017). Social media advertising: Factors influencing consumer ad avoidance. *Journal of Customer Behaviour*, 16(2), 183–201.
[27] Goldfarb, A., & Tucker, C. (2011). Rejoinder—implications of "online display advertising: Targeting and obtrusiveness" . *Marketing Science*, 30(3), 413–415.
[28] Hong, J., & Desai, K. K. (2020). Variety-seeking behavior and information processing in choosing a vacation destination. *Journal of Travel Research*, 59(5), 850–863.
[29] Hossain, M. T. (2018). How cognitive style influences the mental accounting system: Role of analytic versus holistic thinking. *Journal of Consumer Research*, 45(3), 615–632.
[30] Huang, P., Lurie, N. H., & Mitra, S. (2009). Searching for experience on the web: An empirical examination of consumer behavior for search and experience goods. *Journal of Marketing*, 73(2), 55–69.
[31] Hur, S., Lee, J. E., & Stoel, L. (2020). Fair trade advertising: Influences of information type and emotional appeal congruency. *Journal of Marketing Communications*, 26(2), 186–206.
[32] Jung, J. M., Chu, H., Min, K. S., & Martin, D. (2014). Does telic/paratelic

user mode matter on the effectiveness of interactive internet advertising? A reversal theory perspective. *Journal of Business Research*, 67(6), [33] Kanuri, V. K., Chen, Y., & Sridhar, S. (2018). Scheduling content on social media: Theory, evidence, and application. *Journal of Marketing*, 82(6), 89-108.
[34] Kim, D. H., Sung, Y. H., Lee, S. Y., Choi, D., & Sung, Y. (2016). Are you on timeline or news feed? The roles of facebook pages and construal level in increasing ad effectiveness. *Computers in Human Behavior*, 57(4), [35] Kim, J., Lee, J., & Chung, Y. J. (2017). Product type and spokespersons in native advertising-the role of congruency and acceptance. *Journal of Interactive Advertising*, 17(2), 109-123.
[36] Kim, K., & Meyers-Levy, J. (2008). Context effects in diverse-category brand environments: The influence of target product positioning and consumers' processing mind-set. *Journal of Consumer Research*, 34(6), 882-896.
[37] Kim, S., Youn, S., & Yoon, D. (2019). Consumers' responses to native vs. banner advertising: Moderation of persuasion knowledge on interaction effects of ad type and placement type. *International Journal of Advertising*, 38(2), 207-236.
[38] Kwon, K.-N., & Jain, D. (2009). Multichannel shopping through nontraditional retail formats: Variety-seeking behavior with hedonic and utilitarian motivations. *Journal of Marketing Channels*, 16(2), [39] Le-Rademacher, J. G., Peterson, R. A., Therneau, T. M., Sanford, B. L., Stone, R. M., & Mandrekar, S. J. (2018). Application of multi-state models in cancer clinical trials. *Clinical Trials*, 15(5), 489-498.
[40] Lee, D., Hosanagar, K., & Nair, H. S. (2018). Advertising content and consumer engagement on social media: Evidence from facebook. *Management Science*, 64(11), 5105-5131.
[41] Li, J., Luo, X., Lu, X., & Moriguchi, T. (2021). The double-edged effects of e-commerce cart retargeting: Does retargeting too early backfire? *Journal of Marketing*, 85(4), 123-140.
[42] Liberali, G., & Ferecatu, A. (2022). Morphing for consumer dynamics: Bandits meet hidden markov models. *Marketing Science*, 41(4), 235-441.
[43] Liu, Z., del Rosario, M., & Ding, Z. (2021). A markovian model-driven deep learning framework for massive mimo csi feedback. *IEEE Transactions on Wireless Communications*, 21(2), 1214-1228.
[44] Monga, A. B., & John, D. R. (2008). When does negative brand publicity hurt? The moderating influence of analytic versus holistic thinking. *Journal of Consumer Psychology*, 18(4), 320-332.
[45] Montoya, R. M., Horton, R. S., Vevea, J. L., Citkowicz, M., & Lauber, E. A. (2017). A re-examination of the mere exposure effect: The influence of repeated exposure on recognition, familiarity, and liking. *Psychological Bulletin*, 143(5), 459-489.
[46] Nejati, J., & Balasubramanian, A. (2016). An in-depth study of mobile browser performance. Paper presented at the Proceedings of the 25th International Conference on World Wide Web. 1305-1315.
[47] Netzer, O., Lattin, J. M., & Srinivasan, V. (2008). A hidden markov model of customer relationship dynamics. *Marketing Science*, 27(2), 185-204.

[48] Niu, X., Wang, X., & Liu, Z. (2021). When i feel invaded, i will avoid it: The effect of advertising invasiveness on consumers' avoidance of social media advertising. *Journal of Retailing and Consumer Services*, 58(1), 102320.
[49] Oliveira-Castro, J. M., & Foxall, G. R. (2017). Consumer maximization of utilitarian and informational reinforcement: Comparing two utility measures with reference to social class. *The Behavior Analyst*, 40(2), [50] Pieters, R., & Wedel, M. (2004). Attention capture and transfer in advertising: Brand, pictorial, and text-size effects. *Journal of Marketing*, 68(2), 36–50.
[51] Rezaei, S., Ali, F., Amin, M., & Jayashree, S. (2016). Online impulse buying of tourism products: The role of web site personality, utilitarian and hedonic web browsing. *Journal of Hospitality and Tourism Technology*, 7(1),
[52] Romberg, A. R., Tulsiani, S., Kreslake, J. M., Miller Lo, E. J., Simard, B., Rask, A., Arismendez, S. V., Vallone, D. M., & Hair, E. C. (2020). Effects of multiple exposures and ad-skipping behavior on recall of health messages on youtubetm. *International Journal of Environmental Research and Public Health*, 17(22), 8427–8435.
[53] Ruiz, S., & Sicilia, M. A. (2004). The impact of cognitive and/or affective processing styles on consumer response to advertising appeals. *Journal of Business Research*, 57(6), 657–664.
[54] Sahni, N. S., & Nair, H. S. (2020). Sponsorship disclosure and consumer deception: Experimental evidence from native advertising in mobile search. *Marketing Science*, 39(1), 5–32.
[55] Semaan, R. W., Gould, S., Chao, M. C.-h., & Grein, A. F. (2019). "We don' t all see it the same way" : The biasing effects of country-of-origin and preference reversals on product evaluation. *European Journal of Marketing*. 53(5), 989–1014.
[56] Seyedghorban, Z., Tahernejad, H., & Matanda, M. J. (2016). Reinquiry into advertising avoidance on the internet: A conceptual replication and extension. *Journal of Advertising*, 45(1), 120–129.
[57] Sharma, P., Sivakumaran, B., & Marshall, R. (2010). Impulse buying and variety seeking: A trait-correlates perspective. *Journal of Business Research*, 63(3), 276–283.
[58] Siefert, C., Gallent, J., Jacobs, D., Levine, B., Stipp, H., & Marci, C. (2008). Biometric and eye-tracking insights into the efficiency of information processing of television advertising during fast-forward viewing. *International Journal of Advertising*, 27(3), 425–446.
[59] Speck, P. S., & Elliott, M. T. (1997). Predictors of advertising avoidance in print and broadcast media. *Journal of Advertising*, 26(3), 61–76.
[60] Teixeira, T. S., Wedel, M., & Pieters, R. (2010). Moment-to-moment optimal branding in tv commercials: Preventing avoidance by pulsing. *Marketing Science*, 29(5), 783–804.
[61] Thompson, D. V., & Hamilton, R. W. (2006). The effects of information processing mode on consumers' responses to comparative advertising. *Journal of Consumer Research*, 32(4), 530–540.
[62] Villas-Boas, J. M., & Yao, Y. (2021). A dynamic model of optimal retargeting. *Marketing Science*, 40(3), [63] Wang, P., Xiong, G., & Yang, J.

(2019). Serial position effects on native advertising effectiveness: Differential results across publisher and advertiser metrics. *Journal of Marketing*, 83(2), 82-97.
[64] Wojdynski, B. W., Bang, H., Keib, K., Jefferson, B. N., Choi, D., & Malson, J. L. (2017). Building a better native advertising disclosure. *Journal of Interactive Advertising*, 17(2), 150-161.
[65] Wojdynski, B. W., & Evans, N. J. (2016). Going native: Effects of disclosure position and language on the recognition and evaluation of online native advertising. *Journal of Advertising*, 45(2), 157-168.
[66] Wojdynski, B. W., & Evans, N. J. (2020). The covert advertising recognition and effects (care) model: Processes of persuasion in native advertising and other masked formats. *International Journal of Advertising*, 39(1), 4-31.
[67] Yang, D., Lu, Y., Zhu, W., & Su, C. (2015). Going green: How different advertising appeals impact green consumption behavior. *Journal of Business Research*, 68(12), 2663-2675.
[68] Yang, J., & Jiang, M. (2021). Demystifying congruence effects in instagram in-feed native ads: The role of media-based and self-based congruence. *Journal of Research in Interactive Marketing*, 15(4), 685-708.
[69] Yoon, S. (2013). Do negative consumption experiences hurt manufacturers or retailers? The influence of reasoning style on consumer blame attributions and purchase intention. *Psychology & Marketing*, 30(7), 555-565.
[70] Youn, S., & Kim, S. (2019). Newsfeed native advertising on facebook: Young millennials' knowledge, pet peeves, reactance and ad avoidance. *International Journal of Advertising*, 38(5), 651-683.
[71] Yu, J. (2021). A model of brand architecture choice: A house of brands vs. a branded house. *Marketing Science*, 40(1), 147-167.
[72] Zhang, L., Peng, T. Q., Zhang, Y. P., Wang, X. H., & Zhu, J. J. (2014). Content or context: Which matters more in information processing on microblogging sites. *Computers in Human Behavior*, 31(2), 242-249.
[73] Zhou, L., & Xue, F. (2019). In-feed native advertising on news websites: Effects of advertising format, website reputation, and product involvement. *Journal of Internet Commerce*, 18(3), 270-290.
[74] Zhuang, G., Xia, J., Sun, W., Feng, J. e., & Ma, Q. (2021). Asynchronous admissibility and fault detection for delayed implicit markovian switching systems under hidden markovian model mechanism. *International Journal of Robust and Nonlinear Control*, 31(15), 7261-7279.

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Note: Figure translations are in progress. See original paper for figures.