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Study on the Effectiveness of Internet Advertising Based on Consumer Perspectives in Targeting-Challenged Situations

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Abstract. *As internet advertising becomes increasingly prevalent, both consumers and advertisers face new challenges, particularly as the phase-out of third-party cookies has reduced the accuracy of ad targeting. In light of such changes, this study examines the effectiveness of online advertising from the consumer's perspective in targeting-constrained environments. An agent-based simulation model was developed to capture the process from ad exposure to purchase and subsequent sharing. The model incorporates key variables such as interest matching, exposure frequency, and social influence. Simulation results demonstrate that even without precise targeting, ad effectiveness can be improved by aligning content with consumer interests and optimizing exposure frequency. These findings offer practical insights into designing privacy-conscious, user-friendly advertising strategies.*

Keywords: *Agent-based modeling, internet advertising, consumer behavior, advertising effectiveness, repeated exposure*

1. Introduction

As internet usage has become widespread, advertising targeted at internet users has increased. According to a report from the Ministry of Internal Affairs and Communications, over 80% of people in Japan now use the internet. This surge in internet usage has, in turn, accelerated the expansion of online advertising.

As a result, a growing number of companies have entered the internet advertising market. In 2021, expenditures on internet advertising surpassed those on the four traditional mass media—television, newspapers, magazines, and radio. In 2020, spending on internet and mass media advertising was nearly equivalent, but by 2021, internet advertising began to dominate the market, accounting for approximately 40% of total advertising expenditures. These figures demonstrate the steady expansion of the internet advertising market and the frequency with which individuals are exposed to online promotional content.

There are various forms of internet advertising, each associated with different billing models. Common types include listing ads, which appear as text in search engine results (e.g., Google, Yahoo!); display ads, which are shown on websites and applications; and banner ads, which incorporate images or videos. Other forms include affiliate advertising, a performance-based model where advertisers pay only when specific outcomes such as purchases or service usage occur, and native advertising, in which ads are seamlessly integrated into the

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surrounding content. A typical example of native advertising is social media ads, which appear in formats aligned with the content on platforms such as X, Instagram, and LINE. Billing methods also vary depending on the ad type. Cost-per-click (CPC) charges advertisers when an ad is clicked on, while engagement-based billing applies to actions such as likes and reposts on social media. Cost-per-thousand-impressions (CPM) charges advertisers for every 1,000 ad displays, and cost-per-view (CPV) billing applies to video ads when users watch them for a specified duration.

Because internet advertising encompasses a diverse range of formats and features, it offers several advantages compared to more traditional forms of advertising. First, it enables companies to reach a broad audience, both domestically (in Japan) and internationally. Unlike television or outdoor advertisements, which people can see only in certain places at certain times, internet ads can be seen by anyone, anywhere, at any time. Second, internet advertising allows for more efficient budget allocation by targeting users who are more likely to be interested in specific products or services. Thus, advertisers can tailor ad delivery based on demographic attributes such as age or online behavior. Third, the effectiveness of online advertising is easier to measure. Data such as the number of impressions, clicks, or conversions can be recorded and analyzed, enabling firms to evaluate the behavioral impact of their advertising strategies.

However, internet advertising also presents significant challenges, including the spread of scams and misinformation. Some fake ads may promote products using fabricated stories or unauthorized images of celebrities to create false endorsements. Others may direct users to malicious websites. If users visit such websites and share private information (e.g., passwords), they risk identity theft or fraudulent use of their personal data. Thus, internet advertising can pose serious risks to users.

Advertisers themselves are not immune to such harm. Companies may suffer financial losses from fraudulent practices such as "ad fraud," where click counts or impressions are artificially inflated to misrepresent advertising performance, causing advertisers to overpay. In Japan, this problem is widespread: in 2022, the damage from ad fraud rose by 25% from the previous year, reaching 130 billion yen.

As a result of such problems, public concern about privacy protection has grown. In internet advertising, one major change is the phasing out of third-party cookies, which have traditionally been used to track users' browsing behavior and deliver interest-based advertising matched to consumers' likes and actions. The discontinuation of third-party cookies, however, makes it more difficult to deliver ads aligned with users' interests. Consequently, while improved privacy safeguards benefit users, less personalized ads may reduce consumer engagement and purchasing behavior, potentially diminishing companies' profitability. Thus, maintaining effective and relevant advertising under these conditions remains a key challenge for the industry.

Research on internet advertising can be grouped into four areas: evaluating advertising effectiveness, optimizing ad placement, understanding consumer responses to ads, and developing new advertising methods (see Figure 1). The first area, evaluating advertising effectiveness, includes studies that use data-driven models to determine the strength of advertising impact. The second area, optimizing ad placement, uses mathematical models to determine the most efficient allocation of advertising budgets, such as predicting how many users will view an ad relative to expenditure. The third area, understanding consumer responses, often employs surveys to learn about consumers' attitudes and perceptions. Finally, the fourth area, developing new advertising methods, explores innovative ways of delivering ads, such as inserting them at specific moments within videos or utilizing users' location data.

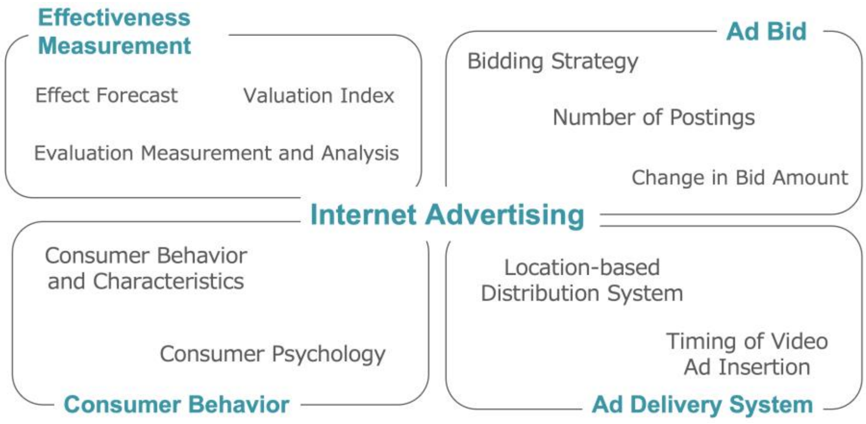

Figure 1.
Classification of internet advertising research

Among these four areas, the first and third evaluating ad performance and analyzing consumer behavior—have received the greatest research attention. This is because they are central to understanding how internet advertising influences product sales and brand success. One reason internet advertising is useful is that it is easily measurable. If companies can measure and predict the power of ads well, they can establish a strong advantage over competitors. Likewise, understanding how advertisements influence consumer attitudes and purchasing decisions is essential for improving advertising strategies and optimizing outcomes.

In the domain of advertising effectiveness, Motohashi et al. (2012) developed a model to estimate how often people would click on banner ads. To do this, they used variables such as the number of impressions, clicks, and subsequent purchases. Similarly, Tagashira et al. (2014) built and tested a model to estimate the likelihood of consumer purchases after ad exposure based on website visit data. These studies primarily use behavioral indicators, such as clicks or purchases, as measures of advertising effectiveness. However, they do not consider the psychological or emotional factors that may motivate these behaviors.

Meanwhile, in the area of understanding consumer responses, Li et al. (2021) studied how people think and feel about internet advertising, identifying several factors contributing to consumers' avoidance of advertising. Furthermore, Adline et al. (2023) developed a model to study how people's feelings about ads and brands can lead to buying behavior. However, while these studies highlight the importance of affective and cognitive processes, they do not clearly demonstrate how these psychological factors translate into measurable advertising effectiveness.

Thus, there are very few studies that simultaneously examine both users' emotional and cognitive responses and the measurable impact of ads. For companies that place ads, understanding whether an ad is effective is closely related to understanding how people feel and behave after seeing the ad. Therefore, it is important to think about both sides—the company and the user—when trying to simultaneously improve advertising performance and enhance user experience.

This study aims to bridge that gap by analyzing how advertising effectiveness varies when viewed from the user's perspective. In the current environment, it has become increasingly difficult to show the right ads to the right people due to individual differences in preferences and growing privacy concerns. As third-party tracking declines, advertisers must find new ways to present relevant ads to diverse audiences. By examining advertising performance in non-targeted settings, this study seeks to generate insights that can inform more effective and user-friendly advertising strategies.

2. Literature Review/ Hypotheses Development

This study draws on several important factors identified in prior research to model and evaluate the effectiveness of internet advertising from the perspective of the consumer. How well an ad matches what the consumer is interested in is an important factor in how effective the ad is. Alalwan (2018) showed that ads that match a person's interests can strongly increase the chance that the person will want to buy the product, especially in the context of social media advertising. Similarly, Mehta et al. (2020) found that personalized ads elicit positive emotions, which in turn increase attention and brand interest.

Another important factor is advertising frequency, the number of times an individual is exposed to a particular ad. Zajonc (1968) proposed that when people see the same ad many times, they start to feel more familiar with it and may like it more. However, if they see the ad too many times, it can lead to ad fatigue and feelings of irritation, thus reducing effectiveness. Furthermore, Kamada et al. (2009) showed that exposure frequency can change which products consumers choose, while Kusumi et al. (2009) found that seeing the same ad repeatedly can evoke feelings of safety and nostalgia.

In recent years, growing attention has also been paid to consumers' privacy concerns. With the rise of targeted advertising and the increased frequency with which consumers are exposed to repeated ads, privacy-related studies have become more prevalent. Odoom (2022) reported that consumers perceive personalized messages as more useful and relevant, yet this personalization can simultaneously heighten privacy concerns. Youn et al. (2019) argued that intrusiveness, clutter, and privacy concerns are closely linked to negative consumer attitudes. Moreover, Morimoto (2021) demonstrated that privacy concerns mediate the relationship between online advertising and consumers' tendency to avoid ads.

Social influence also plays a significant role in shaping online consumer behavior. Word-of-mouth communication and information sharing on social media platforms amplify advertising effects and shape product diffusion. Masuda et al. (2008) employed agent-based modeling (ABM) to show how people's values influence their product selection. In a similar vein, Arai et al. (2012) showed how information spreads through social networks, emphasizing the power of interpersonal connections in shaping consumer awareness.

In addition to these earlier ABM studies on diffusion, more recent simulations have investigated viral marketing dynamics within social networks. For example, Hummel et al. (2012) developed an ABM that examines how interpersonal influence affects product adoption in viral marketing campaigns. Furthermore, Riccardo et al. (2022) incorporated social interactions to probabilistically predict the performance of new products, highlighting the usefulness of ABM in consumer-oriented strategy design.
Collectively, these studies indicate that ABM has been widely applied to word-of-mouth and information diffusion but less frequently to the direct study of internet advertising effectiveness. Prior research has typically examined specific elements—such as user behavior, attitudes toward ads, or social influence—in isolation. Consequently, relatively few studies have simultaneously analyzed both psychological factors (e.g., ad fatigue, interest alignment) and behavioral outcomes (e.g., purchase and sharing behavior), especially in contexts where advertising targeting is constrained by cookie deprecation or privacy regulations.

This study seeks to address that gap. To do this, we employ an agent-based simulation to study internet advertising by looking at many factors at once. Our model shows both how companies choose to show ads and how people see and react to those ads in a case where targeting is not used. Specifically, it accounts for how variables such as ad repetition, relevance, and social influence

interact to affect purchasing and sharing behavior when individual-level targeting is not possible. Based on this framework, the following hypotheses are proposed:
H1: Advertising aligned with site category leads to a higher purchase rate than random ad placement.
H2: Targeted advertising (based on gender preference or site category) yields a higher purchase rate than non-targeted random advertising.

3. Methodology

This study employed an ABM approach to simulate how consumers behave from the moment they view an online advertisement to the point when they purchase the product and potentially share it on social media. We also looked at how advertising outcomes changed under varied conditions. ABM has been increasingly used in social simulation research due to its ability to represent individual behaviors, spatial contexts, and interpersonal interactions. By defining agents and their interactions, ABM enables the representation of complex social dynamics and allows researchers to test numerous "what-if" scenarios.

We developed and implemented the model using the SOARS Toolkit, a library for social simulation made with Java. The SOARS Toolkit is made for ABM and uses agents, spots, roles, rules, and stages. Each agent is a person who makes behavioral decisions within the simulation. Each agent has a role, and roles can change depending on the situation. Each role has its own rules. The rules determine what the agent can do, such as move to a place or make a choice. Spots are places or groups where agents are. For example, a spot can be a location or a social group. Agents can move between spots and make choices based on what other agents do. In this way, the SOARS Toolkit enables the simulation of individual decision-making and information-sharing behaviors, such as how products spread through social media. It also allows for the representation of diverse consumer types, capturing variations in their thinking and actions with relative ease.

Figure 2 presents an overview of consumer behavior as represented in the model. The ABM framework captures the steps people take from seeing an ad to buying the product and sharing it on social media. The model is intentionally designed as an abstract representation, aggregating all types of internet advertising (e.g., display, video, and native ads) into a single category for simplicity. The behavioral process is as follows. First, each consumer decides whether to use the internet. If they do, they choose a website, see ads there, and decide whether to make a purchase based on how they think and feel. At this time, the ad matches the person's type. Then, upon purchase, consumers may share the product information with others online, based on a certain probability. This probability was assigned according to age-specific statistics on information-sharing experiences on social media, reported by the Ministry of Internal Affairs and Communications of Japan. Information diffusion in the model occurs only when a consumer makes a purchase. That is, only agents who have purchased a product or service are eligible to share the information with others. Non-purchasing agents are assumed not to participate in information diffusion. While this may not fully reflect all real-world sharing behaviors, this assumption allows for a simplified analysis of how actual purchasing behavior drives secondary effects such as diffusion.

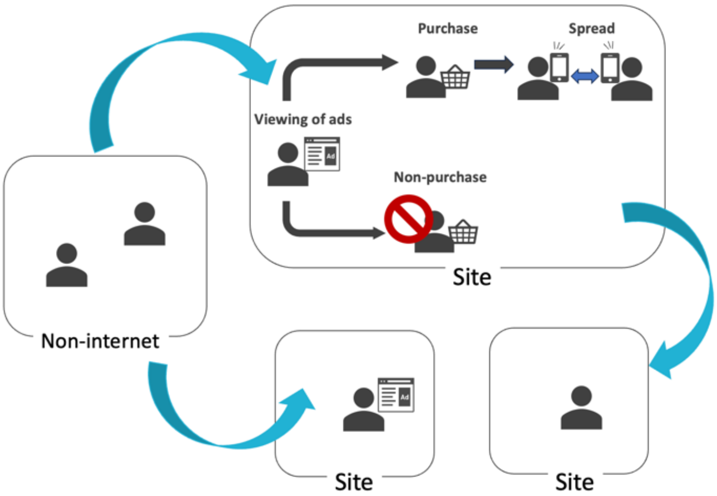

Figure 2.
Overview of consumer behavior in this model

In this model, consumers and advertisements were defined as agents, while websites and non-internet spaces were represented as spots. The list of features assigned to each consumer is shown in Table 1. These features were used to determine behavioral tendencies, such as the probability of internet usage, the likelihood of purchase, and the propensity to share product information. For areas of interest, ten topics were set as shown in Table 2, and these were used to match consumers with ads. For browsing history, we kept information on which sites each consumer had visited. We also separated consumers into two groups: those who used the internet often, and those who did not. Only consumers who used the internet frequently were thought to be more affected by information shared on social media.

Table 1.
Attributes of Consumer Agents

Attribute	Definition
Gender	Male/Female
Age	20s/30s/40s/50s/60s/70s/Over 80s
Purpose of Use	Yes/No
Follower	0/1-5/6-10/11-20/21-30/31-40/ 41-50/51-60/61-70/71-100/101-150/151-200/201-500/501-1000/over 1000
Field of Interest	1-10

A spot in this model represents a website where ads are displayed. Each site was placed into one of the ten interest areas shown in Table 2. Additionally, a non-internet space was defined as a separate spot representing offline environments, where no ads are shown and no information diffusion occurs.

Table 2.
List of Fields of Interest, Sites, and Advertisements

Field	Trend
1	Preferred by men
2	Preferred by men
3	Preferred by women
4	Preferred by women
5	Gender neutral
6	Gender neutral
7	Gender neutral
8	Gender neutral
9	Gender neutral
10	Gender neutral

In this model, a consumer sees an ad, buys a product, and may share it with others. First, the consumer decides whether or not to use the internet, based on age-specific internet usage rates derived from survey data published by the Ministry of Internal Affairs and Communications of Japan. If the internet is not used, the consumer remains in the non-internet space. If the consumer uses the internet, they choose a site to visit. Upon visiting the site, they view the displayed ad, then decide whether to make a purchase. If they buy the product, they may share it with others. After that, they either exit the internet space or visit a new site. This loop makes up one cycle of consumer behavior.

As shown in Table 3, three website selection patterns were modeled to test the impact of targeting on advertising outcomes: random choice, choice based on gender, and choice based on interests. In the random choice pattern, consumers visited websites randomly without any targeting. In the gender-based pattern, some sites were assumed to be visited more by men or women, with each consumer deemed more likely to visit a site that matched their gender. In the interest-based pattern, each consumer's interests were matched with the category of each site.

Table 3.
Site-Selection Rules

Purpose of Use	Site-Selection Rules
Yes	Random site selection
No	Select sites based on gender
No	Select sites based on field of interest
Purpose of Use	Site-Selection Rules
Yes	Random site selection

In addition, the three site-selection rules were implemented based on the consumer's purpose for using the internet. According to Montgomery et al. (2004), an individual's reason for visiting a website reflects their pre-purchase state, which in turn influences purchasing behavior. In this model, when a consumer has a clear reason to use the internet, they are considered to be in the "thinking about buying" stage. At this stage, they often visit sites that match their areas of interest and are more likely to revisit similar sites. Conversely, when a consumer buys a product or repeats the same online activity multiple times, they are then seen as having no clear purpose. In this state, consumers select websites either randomly or based on gender. However, if a consumer in this state visits a site that matches their own interests, they may start to learn more and move into the "thinking about buying" stage again.

In this model, we looked at three main factors that affect a person's decision to make a purchase: whether the ad matches the person's interest, the effect of other people sharing the product, and how many times the ad is seen.

For ad–interest alignment, the model assigned a value of 1 when the advertisement topic matched the consumer's interest area, and 0 when it did not.

For social sharing effects, the model incorporated follower relationships between consumers. If a consumer followed someone who bought and shared a product on social media, that consumer was more likely to be influenced by the shared information when making a purchasing decision. In the model, only consumers who used social media had followers. The number of followers who shared the same ad was used as one of the factors to decide how much influence the shared information had.

For ad exposure frequency, the model applied the "mere exposure effect," whereby repeated exposure increases familiarity and feelings of positivity. Marketing studies often reference the "three-hits" and "seven-hits" theories: the former suggests awareness after three exposures, while the latter indicates higher purchase likelihood after seven. In this model, if an ad was viewed up to three times, the effect became stronger by 0.1 per view. If an ad was viewed four to seven times, the effect became stronger by 0.175 if the ad matched the person's interest, but weaker by 0.2 if it did not. If an ad was viewed eight times or more, the effect became negative (−1), representing irritation or fatigue from irrelevant repetition.

The simulation included 5,000 agents, 10 websites, and 10 ads. Each agent had a follow–follower relationship with other agents. One complete cycle of consumer behavior consisted of the steps described above and was repeated for 100 simulation cycles. The simulation settings are shown in Table 4.

Table 4.
Site-Selection Rules

Item	Value
Number of Agents	5000
Number of Sites	10
Number of Advertisements	10
Number of Simulation Times	100

Using this model, we explored how advertising effectiveness changed depending on how and where ads were shown in each scenario. In Scenario 1, ads that had clear target groups were shown only on websites that matched those groups. For example, ads for men were placed only on websites frequently visited by men, and ads for women were placed only on websites frequently visited by women. All other ads were displayed broadly across websites without changes. In Scenario 2, each ad was shown only on websites within the same interest category. For example, an ad in Category 1 was shown only on Category 1 websites and excluded from any other websites.

4. Findings and Discussion

We first ran the simulation for Scenario 1, which focused on gender-based targeting, where ads were displayed only on websites that matched their intended gender audience.

Figure 3 shows the total number of views for each ad in both the base model and Scenario 1. When there were no restrictions on where ads were shown, each ad received approximately the same number of views. However, when Ads 1 to 4 were shown only on certain websites, the number of times they were viewed decreased significantly. In the same way, Figure 4 presents the purchase rate for each ad in both the base model and Scenario 1. When there were no restrictions on where ads were shown, the purchase rate for each ad was virtually the same, just like the number of views. However, when Ads 1 to 4 were shown only on certain websites, the purchase rate for those ads increased.

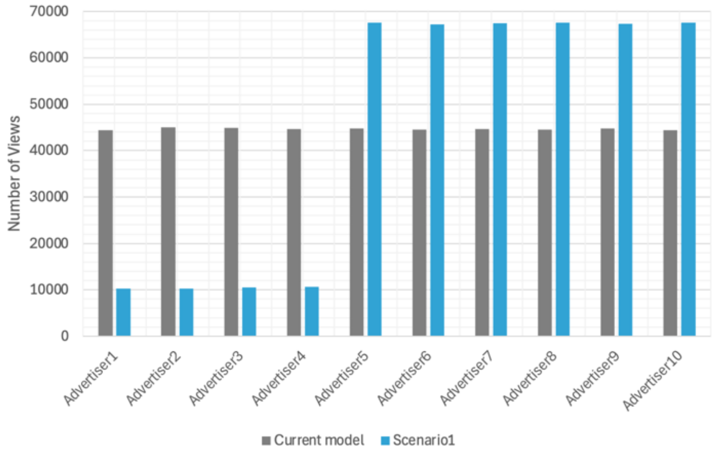

Figure 3.
Number of times each ad was viewed in Scenario 1

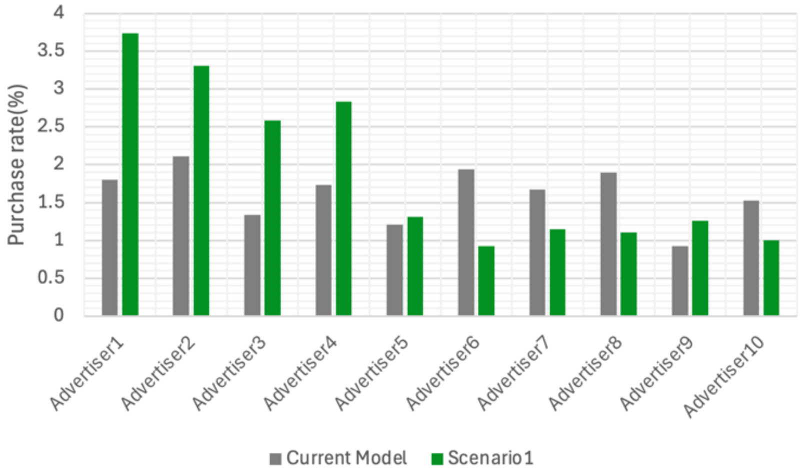

Figure 4.
Purchase rate for each advertisement in Scenario 1

Scenario 2 explored a different approach, in which each advertisement was shown only on websites belonging to the same interest category. Figure 5 shows the total number of times each ad was viewed in both the base model and Scenario 2. Figure 6 shows the purchase rate for each ad in both cases. In Scenario 2, some ads had a higher purchase rate than in the base model, but others had a lower rate. This variation indicates that the effect of category-based targeting differed depending on the specific advertisement.

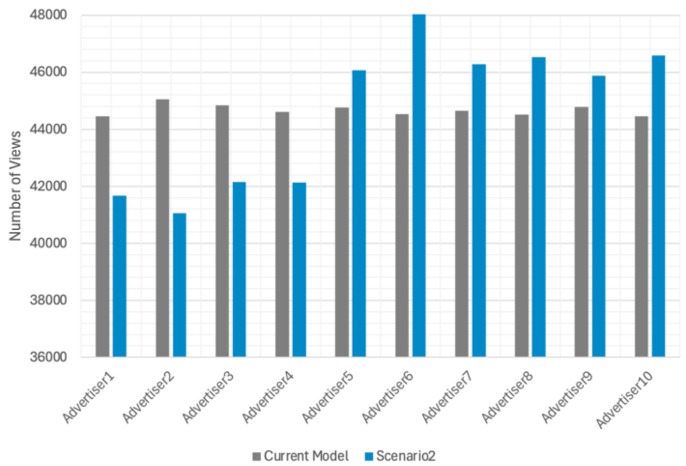

Figure 5.
Number of times each ad was viewed in Scenario 2

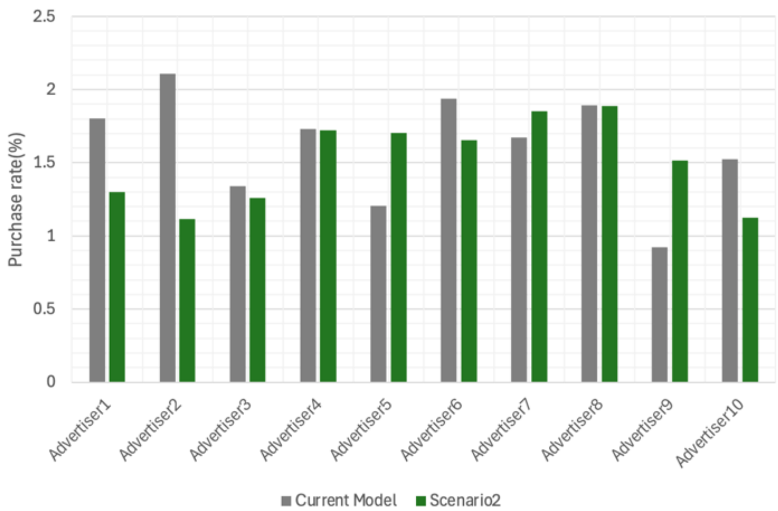

Figure 6.
Purchase rate for each advertisement in Scenario 2

To evaluate the model's validity, we used the purchase rate as an indicator of advertising effectiveness. The purchase rate represented the ratio of user actions—such as product purchases—to the number of ad or website views. These actions may have varied depending on the advertiser's goal, such as purchasing a product or installing an application. In this study, we defined the purchase rate as the number of purchases divided by the number of ad views. Although the rate differs across industries, a typical purchase (or conversion) rate for targeted online advertising is between 1% and 3%. Since this number is based on targeted advertising, where ads are shown to people who are likely to be interested, we made our comparisons under similar conditions.

Accordingly, we ran a simulation that shows the current situation and calculated the average purchase rate for each ad in one cycle. As shown in Scheme 2, the purchase rate was defined as the ratio of the number of purchases to the number of ad views. Although the model did not include monetary values, the frequency of purchase events served as a behavioral indicator of advertising success.

$$Purchase\ rate = \frac{Purchases\ count}{View\ count} \quad (2)$$

The results are presented in Table 5. The average purchase rate for all ten ads was 1.78%. Since this value falls within the 1–3% range typically observed in industry practice, the model can be considered valid.

Table 5.
Purchase Rate for Each Advertisement

Advertisement	Purchase rate (%)
Advertisement1	1.68
Advertisement2	1.54
Advertisement3	1.17
Advertisement4	1.70
Advertisement5	2.08
Advertisement6	2.13
Advertisement7	2.03
Advertisement8	2.10
Advertisement9	1.73
Advertisement10	1.64

This study also examined the effect of repeated ad exposure. As expected, consumers who were exposed to an ad multiple times were more likely to purchase the product, but excessive exposure reduced interest. Figure 7 shows how the total number of purchases changed in each scenario. In the base model, purchases increased slowly over time. In Scenario 2, purchases rose rapidly at the beginning, likely due to a strong match between ads and consumer interests, which enhanced initial engagement. However, as time progressed, the growth rate slowed, suggesting that repeated exposure to the same ad led to fatigue. Since the same ad was repeatedly shown on the same websites, many users encountered it multiple times, reducing novelty and overall effectiveness.

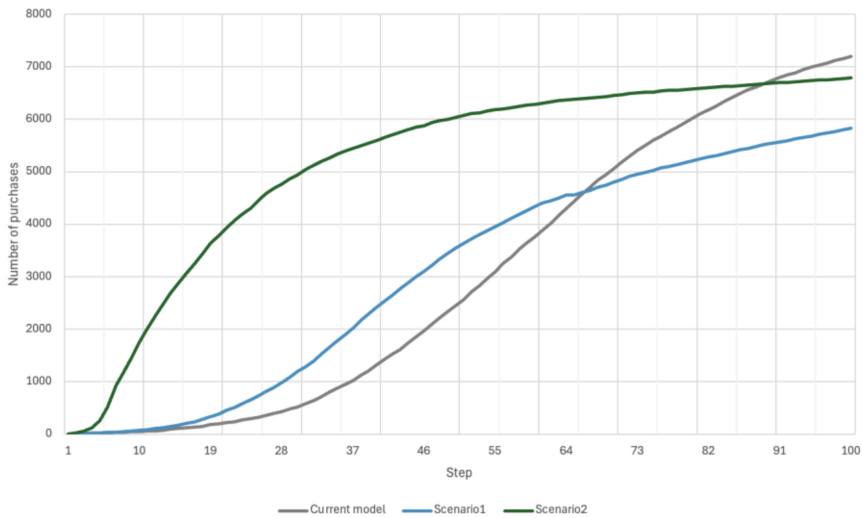

Figure 7.
Cumulative Number of Purchases

This study investigated how the effectiveness of online advertising changes when ad placement strategies are altered, particularly in contexts where direct targeting is limited such as under privacy regulations using ABM. While ABM has been widely applied to simulate consumer behavior and information diffusion on social media, relatively few studies have analyzed advertising strategy or ad effectiveness directly. Moreover, previous studies have rarely examined how repeated ad exposure influences consumer psychology. For example, Masuda et al. (2008) used ABM to model how people's values influence their purchasing decisions, but they did not focus on advertising. Arai et al. (2012) developed a model incorporating consumer networks but only to explore information diffusion in the film industry. Fukunaka et al. (2007) used ABM to study how advertising and pricing affect the market share of products in internet advertising, but, in their model, all consumers responded to ads uniformly, without accounting for individual differences. Therefore, a novel contribution of this study is that it does not focus on a single product or market, and it incorporates psychological factors such as ad fatigue and changing attitudes toward repeated exposure.

Figure 8 presents the distribution of purchase rates for each ad across the three scenarios, based on ten simulation runs with different random seeds. In the base scenario, the width of the distribution was narrow and the variation across seeds was small, indicating that all ads displayed stable purchase rates. In Scenario 1, Ads 1–4 achieved much higher purchase rates due to gender-based targeting. However, the distribution width was wider, suggesting that results fluctuated significantly depending on initial conditions. This implies that Scenario 1 can produce strong positive effects but with low stability.

In contrast, Scenario 2 yielded more consistent outcomes: it improved purchase rates relative to the base model while maintaining stability across runs. Therefore, as an ad strategy, Scenario 1 can be seen as a risky and challenging choice, while Scenario 2 can be seen as a safer but more reliable approach to improving advertising performance.

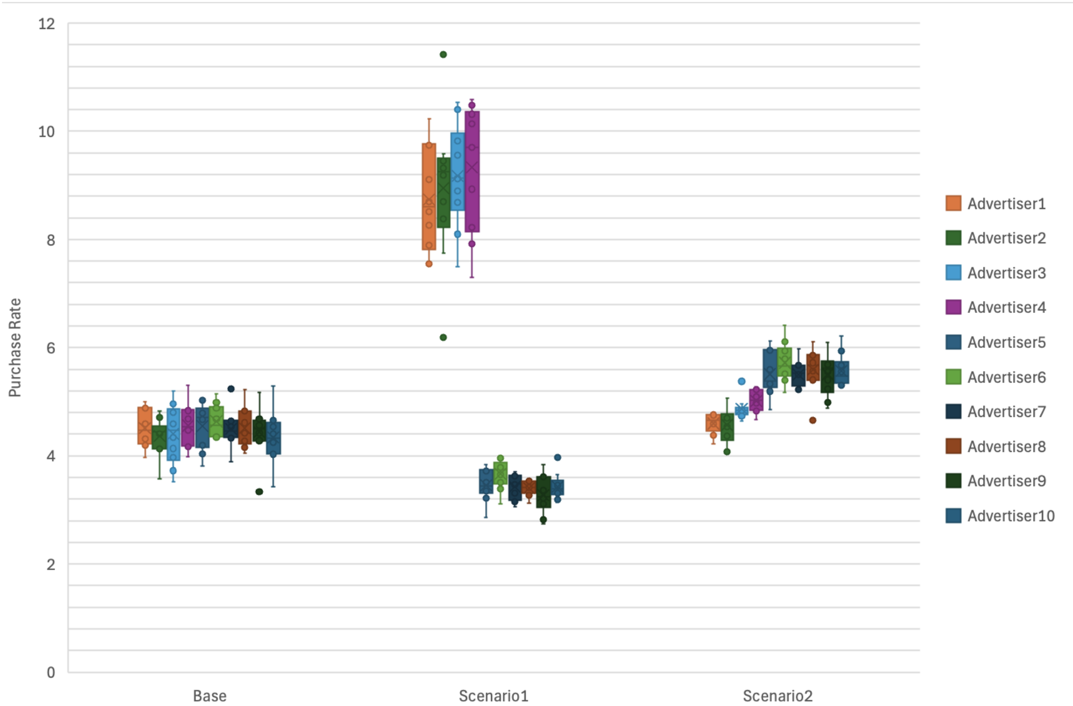

Figure 8.
Purchase Rate by Advertisement And Scenario

5. Conclusions

In this study, we developed a simulation model using ABM to evaluate internet advertising from the consumer's perspective, particularly under conditions where targeted advertising is not possible. Using this model, we explored how advertising effectiveness changes depending on how and where ads are shown. The results indicate that even without direct targeting, it is still possible to reach relevant audiences by carefully aligning ad content with website characteristics. Ads that match the consumer's interests tend to be more effective. However, the way ads are shown can also make people feel uncomfortable. While interest-based advertising can improve engagement, repeated exposure to the same ad or overly personalized messages may lead to negative reactions, such as irritation or fatigue. Therefore, ad placement strategies should strive to balance effectiveness with user experience, ensuring that exposure frequency does not compromise user comfort.

Although the present model provides useful insights, there are still many ways in which it could be improved. For example, the simulation focuses on three main factors ad–interest matching, social influence, and frequency of ad exposure—but it does not account for deeper psychological variables that may also influence purchasing decisions. In addition, consumer diversity is represented only by gender, excluding other important attributes such as age, lifestyle, or socioeconomic background. Furthermore, the current model treats ad exposure frequency as a fixed value. In future work, this could be made more realistic by applying a probability distribution, such as a normal distribution centered around typical exposure frequencies (e.g., eight views). Since this model is designed as a generalized framework rather than for a specific product or market, it can be adapted to various contexts. However, the relationship between ad frequency, product type, and consumer response is likely to differ across markets. In future studies, the model could be improved by incorporating these points, enabling better advertising strategies to be implemented while also keeping users more satisfied.

Declarations

Author contribution
All authors contributed equally to this paper and are listed as co-primary contributors. All authors read and approved the final paper.

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Competing interest
The authors declare that they have no conflicts of interest to report regarding the present study.

References

Adeline, B. I., Kay, H. N. N., Tan, G. W.-H., Lo, P.-S., Chaw, L.-Y., & Ooi, K.-B. (2023). A relook at the mobile advertising landscape: What are the new consumer expectations in the retailing industry? *Telematics and Informatics*, 79. Doi: 10.1016/J.TELE.2023.101953

Alalwan, A. A. (2018). Investigating the impa ct of social media advertising on purch ase intention: A study in the retailing in dustry. *International Journal of Information Management*, 42, 65–72. doi: 10.1016/j.i jinfomgt.2018.06.001

Arai, Y., Kajiyama, T., & Ouchi, N. (2012). Th e impact of social networks on diffusio n process: An analysis of consumer be havior model by multi-agent simulation. *Abstracts of the National Research and Pre sentation Conference of the Japan Society for Management Information Sciences*.

Baek, T. H., & Morimoto, M. (2012). Stay aw ay from me: Examining the determinan ts of consumer avoidance of personali zed advertising. *Journal of Advertising*, 41 (1), 59–76.

Bleier, A., & Eisenbeiss, M. (2015). The impo rtance of trust for personalized online advertising. *Journal of Retailing*, 91(3), 39 0–409.

Fukunaka, S., Kitanaka, H., Chunhui, X., & S hiba, N. (2007). An analysis of promoti on strategies for products with network externalities. *Abstracts of the National Re search and Presentation Conference of the Jap an Society for Management Information Scien ces*.

Hatakeyama, T., Nishioka, D., & Saito, Y. (2016). A study on improvement of an algorithm for video advertisement insertion using smartphone sensors. *Multimedia, Distributed, Cooperative, and Mobile Symposium*.

Hotta, H., Nozawa, T., & Hagiwara, M. (2008). Location based internet advertisement system using neural network. *Journal of Japan Society for Fuzzy Theory and Intelligent Informatics*, 20(3), 347–356.

Hummel, A., Kern, H., Döhler, A., & Kühne, S. (2012). An agent-based simulation o f viral marketing effects in social netwo rks.

Japan. Ministry of Internal Affairs and Communications. (2024). *Results of the 2023 Communications Usage Trends Survey*. (Document No. 240607_1). Tokyo: Ministry of Internal Affairs and Communications.

Japan. Ministry of Internal Affairs and Communications. (2015). *White Paper on Information and Communications in Japan 2015: Trends in Internet usage*. URL: https://www.soumu.go.jp/johotsusintokei/whitepaper/ja/h27/html/nc242250.html.

Kamada, A., Usui, N., & Yoshino, D. (2009). The mere exposure eff ect in choosing merchandise: An examination of impre ssions and categories of merchandise. *Annual Report of Bunkyo University*, 31

Krugman, H. E. (1972). Why three exposures may be enough. *Journal of Advertising Research*, 12(6), 11–14.

Kusumi, T., Matsuda, K., & Sugimori, E. (200 9). Advertisement and consumer behav ior : Sense of safety and nostalgia by m ere exposure effect. *The Japanese Journal of Psychonomic Science*, 28(1), 142–146.

Lee, J. (2021). Avoiding advertising: Examining the predictors of consumer avoidance of online advertising. Keio Media and Communications Research: Annals of the Institute for Journalism, *Media & Communication Studies*, 71, 117–130.

Mariko M. (2021). Privacy concerns about personalized advertising across multiple social media platforms in Japan: the relationship with information control and persuasion knowledge. *International Journal of Advertising, 40(3)*, 431-451. doi: 10.1080/02650487.2020.1796322

Masuda, H., Uemura, R., & Takeshi, A. (200 8). An agent-based model of consumer behavior considering social networks: Applied to the digital music player mar ket. *Journal of the Japan Society for Manage ment Information*, 17(1), 1–23.

Montgomery, A. L., Li, S., Srinivasan, K., & Liechty, J. C. (2004). Modeling online browsing and path analysis using clickstream data. *Marketing Science*, 23(4), 579–595. doi: 10.1287/mksc.1040.0073

Motohashi, E., Isozaki, N., Nagao, H., & Higuchi, T. (2012). Predicting click rates for internet advertisements using state space models. *Operations Research as a Management Science*, 57(10), 574–583.

Odoom, P. T. (2022). Personalised Display Advertising and Online Purchase Intentions:. *International Journal of E-Services and Mobile Applications. 14(1)*, doi: 10.4018/IJESMA.296575

Ono, I., Ishikawa, M., & Deguchi, H. (2020). Proposal of SOARS Toolkit for large-scale agent-based simulation. *The Society of Instrument and Control Engineers*.

Pechmann, C., & Stewart, D. W. (1989). Adve rtising repetition: A critical review of w earin and wearout. *Current Issues and Res earch in Advertising*, 11(2), 285–329.

Reena, M., & Udita, K. (2020). Impact of per sonalized social media advertisements o n consumer purchase intention. Annals of "Dunarea de Jos" University of Ga lati, Fascicle I. Economics and Applied Informatics, 26(2), 15–24. doi: 10.3521 9/eai15840409101

Riccardo Parviero, Kristoffer H. Hellton, Ola Haug, Kenth Engø-Monsen, Hanne R ognebakke, Geoffrey Canright, Arnold o Frigessi, Ida Scheel. (2022). An agent -based model with social interactions f or scalable probabilistic prediction of p erformance of a new product. Internat ional *Journal of Information Management D ata Insig*hts, 2, 100127.

Shiraishi, R. (2018). A bidding strategy of advertising agency in internet advertising auctions. Bulletin of Graduate Studies. *Science and Engineering*, 48.

Sprocket Corporation. (2022, August 9). *What is the average CVR (conversion rate)? Survey data by industry and ideas on target values*. [Web site]. Retrieved from https://www.sprocket.bz/blog/20220809-cvr-average.html

Tagami, Y., Ono, S., & Tajima, A. (2014). Elementary evaluation of CVR prediction models for online advertising. *DEIM*.

The Nikkei. *Advertising and viewer padding scams expanded, with domestic losses totaling 130 billion yen last year*. [Web site]. (2022). Retrieved from https://valuesearch.nikkei.com/popup?keyBody=NIKNWSDGXZQOUC20CO4020122022000000&articleId=NIKNWSDGXZQOUC20CO4020122022000000

The Nikkei. *Internet advertising expenditures surpassed total of four media, including TV, for first time*. [web site]. (2022). Retrieved from https://www.nikkei.com/article/DGXZQOUC244UW0U2A220C2000000/

unidoa. (2024). What are the Seven Hits Theory and the Three Hits Theory. [Web site]. Retrieved from https://unidoa.com/column/7-hit-theory

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. doi: 10.1080/02650487.2019.1575109

Zajonc, R. B. (1968). Attitudinal effects of mere exposure. *Journal of Personality and Social Psychology*, 9, 1–27. doi: 10.1037/h0025848