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Research Article

Algorithmic Marketing Intensity and Consumer Resistance in AI-Driven Advertising: A PLS-SEM Analysis of Social Media Users

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ABSTRACT

Introduction: The increased application of Artificial Intelligence (AI) and algorithmic processes has changed the nature of digital advertising by creating very personalized marketing messages. Although algorithmic personalization could enhance advertising relevance and interactions, overly algorithmic targeting can also lead to adverse reaction among consumers. **Objectives:** This paper investigates the role of the intensity of algorithmic marketing in resisting consumers in the context of AI-driven advertising. **Theoretical Framework:** Based on psychological reactance theory and technology overload theory, our conceptual model is that the intensity of algorithmic marketing augments the feeling of personalization and cognitive overburden which, in turn, results in consumer resistance and avoidance behavior. **Methodology:** The data was gathered with 400 social media users who had been subjected to personalized digital advertising, and they were examined with the help of Partial Least Squares Structural Equation Modeling (PLS-SEM). **Moderating Variable:** The model also examines how artificial intelligence moderates the negative consumer responses through the moderating role of trust. **Key Findings:** The findings suggest that perceived personalization and cognitive strain caused by the strength of the algorithmic marketing have great influence, leading to consumer resistance and avoidance of ads. In addition, consumer resistance decreases with trust in AI and undermines the connection between cognitive strain and resistance. **Contribution/Significance:** The results add to the literature on algorithmic marketing and consumer behavior by identifying the psychological processes underlying resistance to advertising by AI.

Keywords: Algorithmic Marketing, AI Advertising, Consumer Resistance, Ad Avoidance, Cognitive Strain, PLS-SEM.

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INTRODUCTION

Digital marketing has been greatly revolutionized by Artificial Intelligence (AI) and algorithmic systems in the last decade. In the newer digital platforms, machine learning and big data analytics are being highly used to create automated marketing choices, personalized advertisements and predict customer preferences. Facebook, Instagram, Tik Tok and You Tube are social media platforms that have advanced algorithmic recommendation tools that analyze user behavior and provide highly personalized advertisements. Such technologies can help companies to maximize the impact of advertising, as they allow firms to deliver messages based on their browsing history, preferences, and online interactions (Durai *et al*., 2024; Kubovics, 2024; Mokoena and Obagbuwa, 2025). Companies now implement a dynamically changing automated system of advertising content, timing, and positioning based on predictive analytics. These practices enable marketers to provide more context-sensitive and relevant messages in order to enhance the performance of advertisements and consumer response (Ijomah *et al*., 2024; Yusuf Onifade *et al*., 2024). Consequently, AI-based advertising is one of the main elements of modern digital marketing strategies. Although these benefits are evident, recent studies indicate that overuse of algorithmic personalization can produce some undesired negative outcomes. The current consumers are often subjected to high amounts of personalized advertisement that are produced by automated systems. Though personalization can also make it more relevant, excessive algorithmic targeting can also produce the sense of being spied on, manipulated, or deprived of control (Hardcastle *et al*., 2025; Lee *et al*., 2024). By taking marketing systems as over intrusive or persuasive, consumers can be in a psychological state of discomfort and start resisting the influence of marketing. The digital spheres with constant advertising content and overload of information can cause mental burns and decrease the capacity of consumers to perceive marketing

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messages (Maksi *et al*., 2024; Supriyadi *et al*., 2025). The more the number of advertisements that are generated automatically, the more advanced they are, the more the consumers might be feeling the growing psychological pressure due to constant targeting. The conditions may arouse annoying, distrustful, and evading tendencies to digital advertisements. This leads to the behavior of resistance by consumers such as the ignorance of advertisements, ad-blocking software, or even negative attitude towards brands and platforms. Consumer resistance is a famous topic in marketing and persuasion research due to an attitude to appear to be threatened by autonomy or freedom of choice (Fransen *et al*., 2015; Pavey and Sparks, 2009). The resistance to AI-driven advertising can come up in algorithmic marketing settings where consumers can view the use of AI-driven advertising as being overly persuasive or intrusive. Despite the increasing academic interest in algorithmic marketing, the available research has concentrated mostly on the beneficial outcomes of the personalization process, including higher relevance and purchase intention. The possible adverse psychological impact of algorithmic marketing intensity has been relatively scarcely studied, especially in the case of social media advertising. Furthermore, very little is said about the processes, according to which algorithmic targeting causes cognitive strain and consumer resistance. The need to close this gap can be explained by the fact that excessive individualization can undermine consumer confidence and lower the efficiency of digital advertising strategies. In contrast to the previous studies that focus on the positive outcomes of personalization, the current study aligns the concept of algorithmic marketing intensity to show how the overuse of algorithmic targeting can become the cause of cognitive dissonance and consumer backlash. This is a more detailed explanation of consumer behavior towards algorithmic persuasion using this theoretical integration. Third, the research also advances the body of information systems and digital marketing research by illustrating the moderating role of trust in artificial intelligence where consumer trust has the potential to reduce resistance to algorithmic advertising. This research gap is filled by establishing the effect of algorithmic marketing intensity on consumer resistance in an AI-driven advertising setting. Based on both the psychological reactance theory and technology overload theory, we develop a conceptual framework, which suggests that the level of algorithmic marketing is positively correlated with the perceived level of personalization and cognitive strain, which subsequently results in consumer resistance and ad avoidance behavior. Also, the research discusses how trust could be the moderating factor to counteract the adverse reactions of consumers to algorithmic marketing.

LITERATURE REVIEW

Algorithmic Marketing Intensity

Algorithms marketing can be defined as the application of artificial intelligence, machine learning, and data analysis in order to automate marketing decisions and customize customer communications. Algorithms are rapidly becoming more and more a part of how digital platforms examine consumer behavior and provide target advertising messages on a real-time basis. Through these technologies marketers can anticipate the preferences of consumers and maximize the effect of advertising based on the big data of behavior (Theodorakopoulos *et al*., 2025). Artificial intelligence has recently achieved a lot; therefore, digital marketing systems have grown in terms of their capabilities. Predictive analytics, recommendation engines, and automated content-generating AI-powered platforms are now used to generate extremely personalized advertising experiences (Gowri, 2024). The developments enable companies to deliver marketing messages which are personalized to each consumer, which enhances advertising efficiency, and consumer interaction.

The intensity of the algorithmic marketing is a measure of how companies are dependent on the work of automated algorithms to personalize and convey marketing messages. With a growing volume of consumer information on digital platforms, marketers are able to implement more advanced types of personalization techniques that dynamically change based on the browsing profiles and actions of users. Evidence demonstrates that personalization through the use of algorithms may enhance the relevance of advertising and purchase intent because it matches the advertising message to the interests of customers (Beyari and Hashem, 2025).

Nevertheless, the increasing application of algorithmic decision-making in marketing also prompts the issue of autonomy and privacy of a consumer. When consumers feel that the advertising algorithms are too intrusive or manipulative, they may feel uncomfortable. To this end, algorithmic marketing practices can result in both a beneficial and adverse response by consumers based on the perception of what personalization means (De Keyzer *et al*., 2021).

Personalization in AI-Driven Advertising

Individualization has become a leading characteristic in the sphere of digital marketing. The use of personalized advertising is based on the vast consumer information used to tailor marketing messages to individuals as per their preferences and consumer behavior patterns. Artificial-intelligence-based advertising models procedurally analyze big data, such as browsing history, purchase history, social media behavior, etc., to create highly personalized marketing content. Empirical evidence suggests that this kind of personalization will increase the effectiveness of marketing by increasing the perceived relevance of advertising messages. In case the advertisements are relevant to the interests of the consumers, people are more willing to follow the content and think about the advertised products (Babadoğan, 2024). AI-powered technologies additionally extend those features by allowing marketers to automate the individualization workflow and to advantageously advertise advert contextually in real-time.

Recent research highlights the importance of the potential of algorithmic personalization on influencing consumer involvement and buying behavior in digital ecosystems. One-to-one advertising has been established to enhance the perception of creativity, authenticity, and relevance and as a result enhance the willingness of consumers to engage in marketing messages. However, the advantages of personalization are mitigated by the issue of privacy and the use of data. The marketing systems based on AI rely on consumer data collection and analysis in high amounts, which may create the illusion of surveillance in the users. As a result, consumers can have an ambivalent reaction to personalized advertising by valuing its relevance and at the same time feel uncomfortable with the data practices on the background (Rana and Arora, 2021; Rohit *et al*., 2025).

Cognitive Strain in Digital Advertising Environments

Online spaces place consumers in an environment with enormous amounts of information, messages, and advertisements. Constant exposure to personalized marketing messages can create cognitive strain, which can be characterized as a psychological burden of processing too much information. This strain is exhibited whereby people face a state of mental exhaustion due to high rates of informational stimuli.

Information overload has been a salient problem in the digital environment. The more advertising and promotional messages are displayed to the users, the larger they become, and the smaller the cognitive processes of marketing information processing might become. In cases where consumers feel that they are exposed to advertisements too often, or even too intensely, it can be irritating or mentally exhausting (Dai *et al*., 2020). This can be enhanced by algorithmic marketing systems which are constantly providing personalized advertisements based on user behavior. With advertising exposure being optimized by the algorithms to maximize the engagement, consumers might find themselves subjected to repetitive or persistent marketing messages in various platforms, and thus the psychological strain might be higher, and the ability to process the advertising information may be reduced.

Cognitive strain therefore may negatively affect the consumer attitude to advertising and increase the chances of resisting the advert. Consumers perceive targeted advertising as overwhelming and can therefore turn to avoidance techniques to limit the exposure to marketing messages.

Consumer Resistance to Algorithmic Persuasion

Consumer resistance can be defined as behavior or attitudinal reactions to the marketing influence. Resistance will also occur when the consumers feel that the marketing strategies are manipulative, intrusive, or threatening their freedom. Online, resistance is often expressed by behavior, including not looking at adverts, not reading promotional messages, or using ad-blockers. Empirical studies in the area of persuasion and advertising show that consumers develop resistance once they perceive effort to influence their behavior. Persuasion Knowledge Theory argues that people use their knowledge of marketing strategy to decode and react to advertisement messages (Janssen *et al*., 2016). The consumers develop increased skepticism to personalized advertisements when they realize that they are being targeted using algorithms. The latest research on algorithmic persuasion demonstrates that the reaction to algorithm-based marketing depends on such factors as trust, perceptions of fairness, and perceptions of autonomy. There are indicators that consumers can be opposed to AI-driven personalization when they perceive the threat as algorithms to their self-identity or autonomy.

Moreover, algorithmic marketing has the potential to cause complex emotional responses in consumers, including curiosity, excitement, frustration, and distrust. Such emotional feelings help to regulate how people perceive algorithmic suggestions and the advertising content (Caldwell *et al*., 2010). With the increasing integration of algorithmic systems into the mundane digital life, the understanding of consumer resistance to algorithmic persuasion has become a research priority.

Theoretical Background

This study draws on psychological reactance theory and technology overload theory to explain consumer responses to algorithmic marketing. These theories provide complementary perspectives for understanding how excessive algorithmic advertising may trigger negative psychological reactions among consumers.

Psychological Reactance Theory

Psychological reactance theory assumes that psychological arousal occurs when a person believes that his or her freedom or autonomy is threatened (Oh *et al*., 2025). People feel that their freedom of choice is under threat and, therefore, they might be opposed to persuasion in order to recover their freedom. The behavior of resistance can be realized in marketing situations where advertising practices can be regarded as being overly manipulative or intrusive by the consumers.

Recent studies indicated that algorithmic personalization may provoke reactance reactions in case consumers feel that automated systems are too much affecting how they make decisions. Advertising systems that are driven by AI tend to rely on behavioral data and predictive analytics to provide extremely targeted marketing messages. These systems are more relevant, but they can also generate the impression that algorithms are trying to direct or manipulate consumer behavior (Babadoğan, 2024; Hardcastle *et al*., 2025). With the rise in the intensity of algorithmic marketing, customers can turn out to be conscious of the persuasion practices woven into the digital advertising space. Such awareness has the potential to trigger the persuasion knowledge and create resistance responses including skepticism, irritation, and ad avoidance (Janssen *et al*., 2016). Thus, the psychological reactance theory has a significant contribution to the comprehension of how algorithmic marketing practices can result in consumer resistance.

Technology Overload Theory

Technology overload theory states that the overload of digital stimuli leads to cognitive dissonance and psychological pressure in the users of technology. The digital space overwhelms people with large amounts of information, constant messages, and advertisements, and in many cases, it exceeds the processing power of the cognitive systems of the users (Tian *et al*., 2025).

The example of algorithmic marketing systems in the modern context of social media continuously emits individual advertisements based on the behavioral information and preferences of the user. Although this kind of personalization makes the advertising process more effective, recurring exposure to targeted ads can increase the cognitive load required to process a marketing message (Pahari *et al*., 2024). This continued exposure may cause cognitive exhaustion, irritability, and reduce attention to ad content with time (Tian *et al*., 2025). In situations where consumers experience cognitive strain that can be attributed to overexposure to advertisements, consumers can develop coping strategies that would help reduce psychological discomfort. The avoidance of advertising is one of the most common strategies whereby the consumers intentionally avoid or block advertisement messages. As a result, the technology overload theory provides an effective model of thinking about the potential role of the strength of the algorithmic marketing in creating resistance behavior indirectly through cognitive strain.

It will be argued in this paper by combining the psychological reactance theory with the technology overload theory that increased emotion of algorithmic marketing strength increases the perception of personalization and cognitive strain both of which lead to consumer resistance and advertising avoidance behavior.

Research Model and Hypotheses

Based on the theoretical background and literature review, this study proposes a conceptual model explaining how algorithmic marketing intensity influences consumer resistance in AI-driven advertising environments. The model examines the relationships among algorithmic marketing intensity, perceived personalization, cognitive strain, consumer resistance, and ad avoidance behavior. In addition, the model incorporates trust in artificial intelligence as a moderating variable.

Algorithmic Marketing Intensity and Perceived Personalization

Algorithms marketing systems are based on the use of artificial intelligence and data analytics, which provide specific marketing messages. With companies expanding the use of algorithmic decision-making in advertising, consumers are becoming increasingly aware of these advertisements as very customized to their preferences and behavior. Advertising personalization increases the relevance of the message and improves the interaction with the consumers by matching the marketing message and the personal interests (Gu and Duan, 2024; Hardcastle *et al*., 2025).

The behavioral patterns are continuously analyzed using the data concerning consumers, and algorithmic systems make appropriate changes to the advertising content. Therefore, high scores in the intensity of algorithmic marketing will increase the perceptions of consumers that advertising messages are unique and personalized to their needs.

H1: Algorithmic marketing intensity positively influences perceived personalization.

Perceived Personalization and Cognitive Strain

The necessity to increase the relevance by personalized advertising is supplemented by significant risk of creating cognitive strain. The extremely targeted advertising requires consumers to interpret marketing messages which become increasingly complex and individualized. The emergence of more personalized promotions will most likely lead to mental exhaustion caused by excessive exposure to personalized ads by the consumer (Tian *et al*., 2025). The empirical evidence shows that too much online stimuli can result in information overload and cognitive overload in the online space (Chandra *et al*., 2022; De Keyzer *et al*., 2015; Mo *et al*., 2023). Upon exposure to large amounts of individualized advertisements on digital platforms, consumers might experience overwhelmed with the insistent need to analyze and react to advertising communications (Lee *et al*., 2024). Therefore, the increased perceptions of personalization can increase cognitive strain on digital advertising ecosystems.

H2: Perceived personalization positively influences cognitive strain.

Cognitive Strain and Consumer Resistance

Consumer attitude to advertising may be affected by cognitive strain and result in resistance behavior. People who become psychologically fatigued due to overload of information can seek to curtail information sources to the causes of the stressful situation (Bauer and Johnson, 2024). In internet marketing, it can be neglecting adverts, acquiring bad perception towards advertisement, or switching off marketing communication. The studies of consumer behavior and persuasion suggest that cognitive overload triggers negative judgments of the ad information (De Keyzer *et al*., 2021; Janssen *et al*., 2016). When consumers feel that they have been bombarded with repetitive advertising they can develop immunity to marketing influence.

H3: Cognitive strain positively influences consumer resistance.

Consumer Resistance and Ad Avoidance

Resistance to persuasive communication is often reflected in the behavioral response of consumers intended to reduce the contact to persuasive message. Advertising avoidance is one of the most common reactions during which the consumers ignore, avoid, or block advertisements (Dodoo and Wen, 2019; Janssen *et al*., 2016). In cyberspace, ad avoidance has reached a critical point due to the widespread use of ad-blocking software and the increased awareness of consumers to the policies of targeted advertising. The tendency to avoid promoting messages and limiting the contact with promotional content grows when consumers resist the process of marketing persuasion (Pahari *et al*., 2024).

H4: Consumer resistance positively influences ad avoidance.

Trust in Artificial Intelligence and Consumer Resistance

Trust forms a critical influencer towards consumer reactions of the algorithmic systems. As soon as the consumers develop trust towards AI-based technologies, they are more likely to accept algorithmic suggestions and advertisement messages tailored to their needs. On the other hand, lower trust is likely to enhance distrust in algorithmic marketing practices (Lv and Huang, 2022). The consumers who trust AI systems are likely to view algorithmic advertising as beneficial instead of being manipulative. In this line, confidence in AI seems to have the power to overcome the resistance of consumers to algorithmic marketing (Ogbaga and Nweke, 2025).

H5: Trust in artificial intelligence negatively influences consumer resistance.

Moderating Role of Trust in Artificial Intelligence

Consumers might trust Artificial Intelligence (AI), which influences their perceptions regarding the intensity of algorithmic marketing (Akbar *et al*., 2024). When people express trust in the AI systems to a high degree, algorithmic advertising will be perceived as beneficial and relevant, thus reducing the likelihood of cognitive strain developing into resistance behaviors (Shin, 2020). On the other hand, people who trust AI less can be more inclined to consider personalized advertising as an intrusion or manipulation (Wortel *et al*., 2024). As a result, AI trust can mitigate the cognitive strain-consumer resistance connection.

H6: Trust in artificial intelligence moderates the relationship between cognitive strain and consumer resistance.

METHODOLOGY

Research Design

The current study adopts the use of a quantitative research design to examine the correlations between the intensity of algorithmic marketing, perceived personalization, cognitive strain, consumer resistance, and avoidance of advertisements in AI-based advertising situations. The information was collected through a survey that was conducted among social media users who are regularly subjected to personalized advertising on online platforms. The evaluation of the conceptual framework involved Partial Least Squares Structural Equation Modeling (PLS-SEM). The method of analysis used in the research is common in information system and marketing research and is suitable in predictive modelling, complex interrelationships, and latent constructs that are operationalized using several indicators. The chosen methodology is particularly appropriate in cases when the research purpose is to evaluate the relationships between constructs and to evaluate the theoretical models in the unexplored realms of study.

Sample and Data Collection

Data were collected through an online survey administered to social media users who regularly interact with digital advertising. Participants were recruited using online distribution channels including social media groups and digital communities. Participation in the survey was voluntary and anonymous. Respondents were informed about the purpose of the study, and their consent was obtained before completing the questionnaire. No personally identifiable information was collected.

The final sample consisted of 400 respondents who reported active usage of social media platforms such as Facebook, Instagram, TikTok, and YouTube. These platforms frequently utilize algorithmic systems to deliver personalized advertising messages, making them appropriate contexts for examining algorithmic marketing intensity. Table 1 presents the demographic characteristics of the respondents.

The demographic distribution indicates that the sample includes a diverse group of social media users across age groups and platforms.

Measurement of Constructs

All constructs were measured using multi-item scales adapted from prior studies in digital marketing and information systems research. Items were measured using a seven-point Likert scale, ranging from 1=strongly disagree to 7=strongly agree. The constructs included in the study are: Algorithmic Marketing Intensity, Perceived Personalization, Cognitive Strain, Consumer Resistance, Ad Avoidance, Trust in Artificial Intelligence.

Algorithmic marketing intensity captures the extent to which consumers perceive advertisements as algorithmically generated and personalized. Perceived personalization measures the degree to which advertising messages are tailored to individual preferences. Cognitive strain reflects the psychological effort associated with processing personalized advertising messages. Consumer resistance captures negative attitudes toward algorithmic advertising, while ad avoidance represents behavioral responses aimed at reducing exposure to advertising messages. Trust in artificial intelligence measures consumers' confidence in AI-driven marketing systems. Table 2 presents the measurement items used in this study.

Data Analysis Procedure

The data analysis was performed in accordance with the two-step Partial Least Squares Structural Equation Modeling (PLS-SEM) procedure described by Hair *et al*. (2022). First, measurement model was analyzed to determine construct reliability and validity which included checking of indicator loadings, Cronbachs alpha, composite reliability, Average Variance Extracted (AVE), discriminant validity as Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratio. The structural model was then tested to test the hypothesized relationship between the latent constructs. It used bootstrapping of 5,000 resamples to determine the statistical significance of the estimated path coefficients. Also, the analysis included the consideration of the coefficient of determination (R^2) predictive relevance (Q^2) and effect size (f^2). This broad-based method helped to conduct a critical evaluation of the measurement characteristics of the constructs as well as the predictive dynamics of the research model.

Findings

This section presents the results of the PLS-SEM analysis. The measurement model was first evaluated to assess reliability and validity, followed by the structural model assessment to test the hypothesized relationships. Additional indicators including R^2, Q^2, and effect sizes (f^2) were examined to evaluate the explanatory and predictive performance of the model.

Table 3 presents the outer loadings of the measurement indicators used to assess the reliability of the reflective constructs. Indicator reliability was evaluated by examining the standardized outer loadings of each item on its respective latent construct. According to (Hair *et al*., 2022), outer loadings should exceed 0.70 to demonstrate adequate indicator reliability. As shown in Table 3, all measurement items exhibit loadings ranging from 0.82 to 0.88**,** which are well above the recommended threshold. These results indicate that each indicator strongly reflects its corresponding construct. In particular, items measuring Consumer Resistance (CR) and Trust in AI (TAI) show the highest loadings, suggesting strong measurement reliability for these constructs. Since all indicator loadings exceed the recommended threshold of 0.70, none of the items were removed from the measurement model. Therefore, the results confirm that the measurement items demonstrate satisfactory indicator reliability, allowing the analysis to proceed to the assessment of convergent and discriminant validity.

Table 4 presents the results of the reliability and convergent validity assessment of the measurement model. Reliability was evaluated using Cronbach's alpha and Composite Reliability (CR). According to Hair *et al*. (2022), both values should exceed the recommended threshold of 0.70 to indicate satisfactory internal consistency reliability. As shown in Table 4, Cronbach's alpha values range from 0.81 to 0.86, while composite reliability values range from 0.89 to 0.90**,** indicating strong internal consistency across all constructs.

Convergent validity was assessed using the Average Variance Extracted (AVE) (Hair *et al*., 2022). Suggest that AVE values should exceed 0.50, indicating that constructs explain more than half of the variance of their indicators. The AVE values in this study range from 0.70 to 0.76**,** exceeding the recommended threshold. Overall, the results confirm that the constructs demonstrate adequate reliability and convergent validity, indicating that the measurement model is satisfactory and suitable for further structural model analysis.

Table 1: Sample Characteristics (*n*=400).

Demographic Variable	Category	Frequency	Percentage
Gender	Male	210	52.5%
	Female	190	47.5%
Age	18-25	150	37.5%
	26-35	140	35.0%
	36-45	70	17.5%
	46+	40	10.0%
Platform	Facebook	180	45.0%
	Instagram	90	22.5%
	TikTok	70	17.5%
	YouTube	60	15.0%

Table 2: Measurement Items.

Construct	Item	Measurement Statement
Algorithmic Marketing Intensity	AMI1	I frequently see advertisements tailored to my interests.
	AMI2	Online ads appear based on my browsing behavior.
	AMI3	Social media platforms track my preferences to show ads.
	AMI4	Advertisements I see are highly personalized.
Perceived Personalization	PP1	The advertisements I see match my interests.
	PP2	Online ads are customized for me.
	PP3	Advertising content reflects my preferences.
Cognitive Strain	CS1	Personalized ads feel overwhelming.
	CS2	I feel mentally tired from repeated targeted ads.
	CS3	Too many personalized ads appear online.
Consumer Resistance	CR1	I feel annoyed by personalized advertising.
	CR2	I distrust algorithm-based advertising.
	CR3	I resist interacting with targeted advertisements.
Ad Avoidance	AA1	I skip advertisements whenever possible.
	AA2	I avoid clicking online ads.
	AA3	I try to ignore digital advertisements.
Trust in AI	TAI1	AI systems provide reliable recommendations.
	TAI2	I trust AI-generated advertising suggestions.
	TAI3	AI technologies generally make good decisions.

Discriminant validity was assessed using the Fornell-Larcker criterion, which compares the square root of the Average Variance Extracted (AVE) of each construct with the correlations between constructs. According to Fornell and Larcker (1981), discriminant validity is established when the square root of AVE for each construct is greater than its correlations with other constructs. As shown in Table 5, the diagonal values representing the square root of AVE (ranging from 0.84 to 0.87) are greater than the corresponding inter-construct correlations. For example, the square root of AVE for algorithmic marketing intensity (0.84) is higher than its correlations with perceived personalization (0.51), cognitive strain (0.40), consumer resistance (0.31), ad avoidance (0.24), and trust in AI (0.11). Similar patterns are observed for all other constructs. These results indicate that each construct shares more variance with its own indicators than with other constructs in the model. Therefore, the Fornell-Larcker criterion confirms that discriminant validity is established for all constructs in the measurement model.

To further assess discriminant validity, the Heterotrait-Monotrait Ratio (HTMT) was examined. The HTMT ratio is considered a more stringent criterion for evaluating discriminant validity in PLS-SEM models (Henseler *et al.*, 2015). According to the recommended threshold, HTMT values should be below 0.85 to confirm adequate discriminant validity. In Table 6, all HTMT values range between 0.17 and 0.74, which are well below the recommended threshold of 0.85. The highest HTMT value is observed between consumer resistance and ad avoidance (0.74), which remains within the acceptable limit. These results indicate that the constructs in the model are empirically distinct from one another. Therefore, the HTMT analysis confirms that discriminant validity is established for all constructs, providing further support for the adequacy of the measurement model.

Table 8 reports the coefficient of determination (R^2) values for the endogenous constructs in the structural model. The R^2 values indicate the proportion of variance in each endogenous construct explained by its predictor variables. According to (Hair *et al.*, 2022), R^2 values of 0.25, 0.50, and 0.75 can be described as weak, moderate, and substantial, respectively. As shown in Table 8, the model explains 26% of the variance in Perceived Personalization (PP), 23% in Cognitive Strain (CS), 31% in Consumer Resistance (CR), and 39% in Ad Avoidance (AA). These results indicate that the model demonstrates weak to moderate explanatory power, with the strongest explanatory capability observed for consumer resistance and ad avoidance. Overall, the findings suggest that the proposed model provides acceptable explanatory power for predicting consumer responses to algorithmic marketing in AI-driven advertising environments, which is consistent with behavioral research models in information systems and digital marketing contexts.

The coefficient of determination (R^2) was used to assess the explanatory power of the structural model. The results show that algorithmic marketing intensity explains 26% of the variance in Perceived Personalization (PP), while perceived personalization explains 23% of the variance in Cognitive Strain (CS) (Table 7). In addition, the model explains 31% of the variance in Consumer Resistance (CR) and 39% of the variance in Ad Avoidance (AA). According to (Hair *et al.*, 2022), R^2 values of 0.25, 0.50, and 0.75 indicate weak, moderate, and substantial explanatory power respectively. Therefore, the model demonstrates moderate explanatory power for key endogenous constructs, particularly for consumer resistance and ad avoidance. Furthermore, the predictive relevance (Q^2) values for all endogenous constructs are greater than zero, indicating that the model has satisfactory predictive relevance. The effect size (f^2) results also show that algorithmic marketing intensity has a substantial effect on perceived personalization, while cognitive strain has a strong effect on consumer resistance. These findings suggest that the proposed model provides meaningful explanatory and predictive insights into consumer responses to algorithmic marketing in AI-driven advertising environments. The model demonstrates acceptable to moderate explanatory power, which is consistent with behavioral research models in information systems and digital marketing contexts (Table 9).

Table 3: Indicator Reliability (Outer Loadings).

Construct	Item	Loading
AMI	AMI1	0.86
AMI	AMI2	0.84
AMI	AMI3	0.83
AMI	AMI4	0.82
PP	PP1	0.85
PP	PP2	0.86
PP	PP3	0.84
CS	CS1	0.87
CS	CS2	0.87
CS	CS3	0.86
CR	CR1	0.88
CR	CR2	0.87
CR	CR3	0.86
AA	AA1	0.86
AA	AA2	0.86
AA	AA3	0.87
TAI	TAI1	0.88
TAI	TAI2	0.87
TAI	TAI3	0.86

All loadings exceed 0.70, confirming indicator reliability.

In Table 10, in addition to Harman's single-factor test, the study applied the full collinearity Variance Inflation Factor (VIF) test proposed by (Kock, 2015) to assess potential common method bias. This approach evaluates whether latent constructs exhibit excessive collinearity that may indicate common method variance. The results show that all VIF values are below the recommended threshold of 3.3, suggesting that common method bias is unlikely to affect the results.

Table 11 presents the effect size (f^2) values, which assess the relative impact of each exogenous construct on the endogenous constructs in the structural model. According to (Hair *et al.*, 2022), f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effect sizes, respectively. As shown in Table 10, algorithmic marketing intensity has a large effect on perceived personalization (f^2=0.35). Similarly, cognitive strain exhibits a large effect on consumer resistance (f^2=0.37), and consumer resistance shows a large effect on ad avoidance (f^2=0.42). These findings suggest that these relationships play a substantial role in explaining consumer responses to algorithmic marketing.

In contrast, perceived personalization demonstrates a medium effect on cognitive strain (f^2=0.30), indicating that personalization contributes moderately to consumers' cognitive strain in digital advertising environments. Finally, trust in AI and the moderating interaction between cognitive strain and trust in AI show small effect sizes (f^2=0.05 and 0.06, respectively), suggesting that

Table 4: Reliability and Convergent Validity.

Construct	Cronbach α	Composite Reliability	AVE
AMI	0.86	0.90	0.70
PP	0.81	0.89	0.73
CS	0.84	0.90	0.75
CR	0.84	0.90	0.76
AA	0.83	0.89	0.74
TAI	0.84	0.90	0.75

Table 5: Fornell-Larcker Criterion.

	AMI	PP	CS	CR	AA	TAI
AMI	0.84					
PP	0.51	0.85				
CS	0.40	0.48	0.87			
CR	0.31	0.35	0.51	0.87		
AA	0.24	0.29	0.44	0.62	0.86	
TAI	0.11	0.08	0.12	-0.06	-0.04	0.87

Table 6: HTMT Ratio.

	AMI	PP	CS	CR	AA	TAI
AMI	-					
PP	0.62	-				
CS	0.52	0.60	-			
CR	0.48	0.51	0.71	-		
AA	0.40	0.44	0.62	0.74	-	
TAI	0.21	0.18	0.23	0.19	0.17	-

Table 7: Coefficient of Determination (R^2).

Endogenous Variable	R^2
PP	0.26
CS	0.23
CR	0.31
AA	0.39

Table 8: Predictive Relevance (Q^2).

Construct	Q^2
PP	0.26
CS	0.23
CR	0.30
AA	0.38

Since $Q^2 > 0$, the model demonstrates predictive relevance.

Table 9: Collinearity VIF Assessment.

Construct	VIF
Algorithmic Marketing Intensity	2.41
Perceived Personalization	2.36
Cognitive Strain	2.55
Consumer Resistance	2.67
Ad Avoidance	2.21
Trust in AI	2.18

Table 10: Effect Size (f^2).

Path	f^2	Effect Size Interpretation
AMI → PP	0.35	Large
PP → CS	0.30	Medium
CS → CR	0.37	Large
CR → AA	0.42	Large
TAI → CR	0.05	Small
CS × TAI → CR	0.06	Small

Table 11: Structural Model Summary.

Hypothesis	Path	Β	*t*-value	*p*-value	f^2	Decision
H1	AMI → PP	0.508	14.248	<0.001	0.35	Supported
H2	PP → CS	0.480	12.045	<0.001	0.30	Supported
H3	CS → CR	0.541	15.232	<0.001	0.37	Supported
H4	CR → AA	0.620	19.849	<0.001	0.42	Supported
H5	TAI → CR	-0.129	3.391	0.001	0.05	Supported
H6	CS × TAI → CR	-0.160	3.834	<0.001	0.06	Supported

although these effects are statistically significant, their substantive impact on consumer resistance is relatively modest. In a nutshell, the effect size results indicate that the strongest influences in the model occur along the path from algorithmic marketing intensity to perceived personalization, cognitive strain to consumer resistance, and consumer resistance to ad avoidance, highlighting the central role of cognitive and behavioral mechanisms in explaining consumer responses to AI-driven advertising.

Table 11 summarizes the results of the structural model analysis, including path coefficients (β), *t*-values, *p*-values, and effect sizes (f^2). The bootstrapping results indicate that all hypothesized relationships are statistically significant, providing support for all proposed hypotheses. Specifically, algorithmic marketing intensity positively influences perceived personalization (β=0.508, *p*<0.001), supporting H1. Perceived personalization also has a significant positive effect on cognitive strain (β=0.480, *p*<0.001), supporting H2. Furthermore, cognitive strain significantly increases consumer resistance (β=0.541, *p*<0.001), confirming H3. Consumer resistance, in turn, has a strong positive effect on ad avoidance behavior (β=0.620, *p*<0.001), supporting H4. In addition, trust in AI negatively affects consumer resistance (β=−0.129, *p*=0.001), indicating that higher levels of trust reduce consumer resistance toward algorithmic advertising, thereby supporting H5. The moderating effect of trust in AI on the relationship between cognitive strain and consumer resistance is also significant ($\beta=-0.160$, $p<0.001$), supporting H6. This finding suggests that trust in AI weakens the positive relationship between cognitive strain and consumer resistance. In brief, the results support all proposed hypotheses, demonstrating that algorithmic marketing intensity increases perceived personalization and cognitive strain, which subsequently lead to consumer resistance and ad avoidance, while trust in AI weakens this relationship.

Having validated the measurement model and confirmed the hypothesized relationships in the structural model, the next section discusses the theoretical and managerial implications of the results.

DISCUSSION AND IMPLICATIONS

This paper has discussed how the level of algorithmic marketing affects consumer resistance in artificial intelligence-based advertising platforms. The proposed model based on the psychological reactance theory and technology overload theory explained the ways the algorithmic marketing practices can cause cognitive strain and resistance behaviors in the consumer. The empirical evidence provides several important conclusions about consumer behavior to algorithmic advertising.

To begin with, the findings show that algorithmic marketing strength has a massive positive impact on the perceived personalization, which confirms H1. This finding is consistent with the previous studies that suggest the impact of algorithmic systems on the provision of personalized advertising information using behavioral data (Bleier and Eisenbeiss, 2015; Lambrecht and Tucker, 2019). With more companies implementing AI-based advertising, consumers are becoming more aware of the fact that marketing advertisements are being adjusted to their preferences and browsing patterns.

Second, the findings show that the perceived personalization has a positive effect on cognitive strain, which confirms H2. Although personalization could assist in improving the relevance of advertising, frequency of personalization could also increase the thinking load one needs to handle the marketing messages. The given observation aligns with studies that implied that personalized advertising repeated exposure could cause information overload in online space (Bright and Logan, 2018).

Third, the cognitive strain is a significant predictor of consumer resistance, which confirms H3. Consumers who are mentally exhausted because of being targeted by advertising frequently tend to develop negative attitudes towards algorithmic marketing. The result supports the technology overload theory that argues that an overload of digital stimuli might lead to psychological stress and reduce user desire to use digital content (Tarafdar *et al*., 2015).

Fourth, the findings validate that H4 is true that consumer resistance causes ad avoidance. In cases where consumers find advertising to be annoying, obtrusive, or overwhelming, they can make active effort to minimize contact with marketing messages, by skipping advertisements, ignoring marketing messages, or by using ad-blocking software. This has been on the rise since the online world where consumers are exposed to regular target advertisements.

Fifth, the study observes that consumer resistance is adversely affected by trust in artificial intelligence and this supports H5. Customers, who have confidence in AI-driven systems, are less likely to consider algorithmic advertising as manipulative and intrusive. Reliability is, therefore, a central aspect that influences consumer perception of algorithmic marketing operations.

Lastly, the findings show that the association between cognitive strain and consumer resistance is mediated by trust in AI, which validates H6. Namely, the intensity of the association between cognitive strain and resistance is being reduced by increased degrees of trust. This observation implies that individuals who have confidence in the use of AI technologies can perceive personalized advertisement as helpful instead of manipulative and, therefore, the resistance behavior propensity decreases.

Theoretical Implications

This research contributes to digital marketing, information systems, and consumer behavior literature in a few ways. To start with, it builds upon past studies on algorithmic marketing by discussing the possibility of adverse effects of too much personalization. Though the previous research primarily focused on the advantages of customized advertising, the current paper demonstrates that consumer opposition to the forces of algorithmic marketing can be elicited by the strength of such advertising using psychological principles. Second, the research combines psychological reactance theory with theory X of technology overload to explain the reaction of consumers towards AI-driven advertising. The combination of these frameworks assists the research in providing a more in-depth picture of the impact of the algorithmic marketing practices on cognitive and behavioral responses. Third, the results enhance the emerging literature on algorithmic persuasion resistance among the consumers. With the further integration of AI technologies into marketing at this point, the further relevance of researchers to the understanding of how consumers perceive and respond to algorithmic decision-making systems increases rapidly.

Managerial Implications

The findings provide useful instructions for the marketers and the platform managers. Firms should exercise caution during the severity of algorithmic customization. Although one-to-one advertising helps increase marketing efficiency, over targeting may overwhelm the customers and diminish the interaction. The companies are also supposed to focus on transparency in AI-based marketing systems. Before reducing perceived manipulation, it is possible to create trust by offering clear descriptions of how user data is used to guide personalization. Marketers are supposed to provide control solutions, including letting users customize their personalization options or disabling targeted advertising. Resistance behaviors can be minimized by having more control by users. Firms ought to make investments in establishing consumer confidence in AI products. Customers would be convinced to embrace individualized advertisements and access digital marketing content when they believe that AI systems are dependable and helpful.

CONCLUSION

This paper has explored the role of the strength of algorithmic marketing and its impact on consumer resistance to AI-based advertising space. Based on psychological reactance theory and technology overload theory, the researchers have suggested and empirically tested a conceptual model, which explains how the practices of algorithmic marketing affect consumer perceptions and behavior. The model examined the interactions between the intensity of algorithmic marketing, perceived personalization, cognitive strain, consumer resistance and avoidance as well as the interactions between trust in artificial intelligence and interactions. The results based on the survey data of 400 participants of social media and the regression analysis with the help of Partial Least Squares of the Structural Equation Modeling (PLS-SEM) provide some important conclusions. To begin with, the increased algorithmic marketing intensity results in an increased feeling of personalization. With the growing use of AI in digital platforms to focus ads, consumers can see that text messages are personally friendly and responsive to their likes and habits. Second, this augmented sense of personalization exerts more cognitive burden. That is, excessive personalized advertising may lead to psychological exhaustion in the Internet environment. Cognitive strain, in its turn, is a strong predictor of consumer resistance towards algorithmic advertising. Whenever individuals are mentally exhausted or frustrated by a series of targeted messages, they are then likely to develop a negative attitude towards advertising. Fourth, consumer resistance is a factor that encourages ad avoidance behavior, as it demonstrates that users can exert effort in attempting to minimize their exposure to advertisements in cases where they perceive marketing activity as intrusive/excessive. Lastly, the results highlight the significant role of trust, which is applicable to AI. Trusting users of AI systems are less prone to resistance to algorithmic advertising and trust undermines the relationship of cognitive strain and consumer resistance, meaning that confidence in AI can reduce the adverse reaction to algorithmic marketing activities.

LIMITATIONS AND FUTURE RESEARCH

Though this research provides useful informational material to the study of consumer responses towards algorithmic marketing, it states a number of limitations. The study relies on self-reported survey information, which may be affected by common methods and perceptual bias. Future research may combine survey instruments with behavioral data of online platforms, including clickstream or online advertisement interactions. Due to the limited scope of the sample, namely, the social media users, the results might not be applicable in other digital settings. Exploring the idea of algorithmic marketing in such applications as e-commerce websites, mobile applications, or streaming products would be useful. The paper has discussed a limited number of psychological processes that lead to consumer resistance. Future studies would be able to research more factors that can affect the reaction to algorithmic advertising, such as privacy, perceived fairness, transparency of the algorithm, perceived manipulation. The presence of cross-cultural variations in the response of consumers to algorithmic marketing is another area that should be explored further. Privacy and autonomy cultural influences, as well as technology acceptance, might influence the way consumers perceive algorithmic personalization. Lastly, longitudinal research may further enhance our knowledge of the dynamic nature of the attitudes towards the concept of algorithmic marketing as the AI technologies will increase their integration into the daily online routine.

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ABBREVIATIONS

AI: Artificial Intelligence; **PLS-SEM:** Partial Least Squares Structural Equation Modeling; **AVE:** Average Variance Extracted; **HTMT:** Heterotrait-Monotrait; **VIF:** Variance Inflation Factor; **AMI:** Algorithmic Marketing Intensity; **PP:** Perceived Personalization; **CS:** Cognitive Strain; **CR:** Consumer Resistance; **AA:** Ad Avoidance; **TAI:** Trust in Artificial Intelligence; **CR:** Composite Reliability.

CONFLICT OF INTEREST

The author declares that there is no conflict of interest.

CONSENT TO PARTICIPATE DECLARATION

Informed consent was obtained from all individual participants included in the study prior to their participation. Participants were informed about the purpose of the research, the voluntary nature of their participation. All responses were collected anonymously, and participants were assured that their data would be kept confidential and used solely for academic purposes.

ETHICAL ISSUES DECLARATION

Ethical approval was obtained from the Independent University, Bangladesh//Institutional Review Board on "No Review Exemption". (Approval No.: 2026-SBE: R06)

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