

Algorithmic Marketing: Consumer Targeting, Optimization, and Performance Outcomes

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ABSTRACT:

Algorithmic marketing has become a critical component of digital advertising, enabling organizations to leverage artificial intelligence (AI), data analytics, and automation to improve targeting precision and campaign effectiveness. This study examines the influence of consumer-targeting characteristics and advertising optimization factors on marketing performance outcomes within an algorithmic marketing framework. Using a quantitative research design, secondary data comprising 9,854 advertising observations were analyzed. Consumer-targeting variables included age, gender, income, and location, while advertising optimization factors comprised ad type, ad topic, and ad placement. Marketing performance was assessed using clicks, click-through rate (CTR), and conversion rate. Multiple linear regression and Random Forest analyses were employed to evaluate explanatory and predictive relationships among the variables. The findings revealed that consumer-targeting and optimization-related factors did not significantly influence CTR or conversion rate, with both regression models exhibiting limited explanatory power ($R^2 = 0.002$). Similarly, the Random Forest model demonstrated weak predictive performance ($R^2 = -0.085$), indicating that the selected variables explained only a small proportion of advertising outcomes. Feature importance analysis identified income and age as the most influential predictors, although their overall contribution remained limited. The results suggest that advertising performance is likely shaped by additional factors, including consumer behavior, contextual influences, platform algorithms, and real-time engagement dynamics. This study contributes to the algorithmic marketing literature by highlighting the limitations of demographic targeting and basic optimization variables and emphasizing the need for more comprehensive, data-rich approaches to understanding digital advertising effectiveness.

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Introduction

The advent of new technologies such as artificial intelligence (AI), machine learning, and big data

analytics (BD) has made Algorithmic marketing a gamechanger in the digital advertising industry (Adikari and Dutta, 2019). Algorithmic systems are being used by organizations increasingly to automate their marketing decisions, optimize their advertising campaigns, and personalize their experiences with consumers (Deckker, 2025). With more data at their fingertips, marketers have created more sophisticated audience targeting strategies using demographic, geographic and behavioral traits, making it easier to reach the right audiences more effectively. The use of AI for personalization has been found to boost customer engagement, making ads more relevant, and deepening customer relationships by delivering targeted messages (Anshari et al., 2019; Bhardwaj et al., 2024). In addition, the ability of organizations to recognize high value segments and make campaigns more effective has been enhanced by integrating clickstream and consumer interaction data (Sakalauskas and Kriksciuniene, 2024).

Optimisation now plays a vital role in contemporary marketing strategies, not just for targeting purposes. By using AI-driven optimization features, companies can fine-tune ad targeting, place ads where they fit best, and distribute resources more efficiently, leading to maximum campaign performance (Achnani, 2025). By continuously testing and adjusting campaigns based on performance metrics and consumer feedback, these optimization strategies help maximize marketing efficiency and effectiveness. By constantly optimizing marketing efforts, continuously testing and fine-tuning campaigns based on performance metrics and consumer response, these practices contribute to a more efficient, effective marketing operation (Shoushtari et al, 2023). As a result, organisations are turning to evidence-based marketing tactics which are based on measurable metrics like clicks, click-through rates (CTR) and conversion rates to measure the success of marketing campaigns and support strategic decision making (Rahman and Hye, 2022).

Existing research has been largely focusing on the issues of targeting consumers and optimization of the campaign separately, even though algorithmic marketing is gaining popularity. There is little

empirical research on the impact of attribute targeting on marketing performance outcomes and how attribute targeting and optimization-related decisions interact. Little empirical research has been conducted on the interaction between attribute targeting and marketing performance outcomes. The present study fills this vacuum by exploring how consumer targeting variables and optimization variables interact in determining advertising effectiveness. The study brings these factors into the algorithmic marketing context and adds to the understanding of the factors that determine the effectiveness of digital advertising, while simultaneously giving practical guidance in making decisions on marketing based on data.

Research Objectives

RO1: To examine the effect of consumer-targeting characteristics on marketing performance outcomes.

RO2: To assess the impact of advertising optimization factors on marketing performance outcomes.

RO3: To identify the key determinants of advertising performance within an algorithmic marketing framework.

2. Literature Review

In today's digital advertising landscape, algorithmic marketing has become a gamechanger due to the advancements in artificial intelligence (AI), machine learning, and big data analytics. Algorithmic marketing is different from traditional marketing methods, which are mostly based on managerial intuition and mass communication strategies, as it employs algorithmic systems to automate decision-making, process consumer data, and optimize advertisements in real time (Dilaver and Dilaver, 2024).

As digital consumer information becomes more widely available and AI technologies are rapidly evolving, organizations can use data-driven strategies to improve their marketing precision and effectiveness (Deckker, 2025). As a result, companies are turning to algorithmic solutions

to enhance their customer acquisition, engagement and conversion results.

Consumer targeting is a pivotal aspect of algorithmic marketing, whereby the search for an audience is narrowed down to specific members of the group based on specific consumer characteristics. With the development of CRM and big data analytics, marketers are now able to create advertising strategies that can be customized to meet individual customers' needs and preferences, which in turn allows them to deliver personalized marketing messages (Anshari et al., 2019). Demographic, geographic and behavioral data are used by AI-driven targeting systems to segment audience and fine-tune advertising relevance (Bhardwaj et al., 2024). Moreover, clickstream and interaction data have improved the capacity of businesses to understand high-value customers and create tailored ads that boost engagement and conversion rates (Sakalauskas and Kriksciuniene, 2024).

Targeted advertising has been shown to make communication more efficient and elicit more consumer reactions due to the elimination of irrelevant messages and information overload (Shin and Yu, 2021). Hence, there is growing awareness that the characteristics of consumers are important factors in advertising effectiveness. Apart from targeting, marketing optimization also makes a significant impact in boosting the performance of campaigns. Optimization is the process of systematically tweaking advertising elements—ad placement, format, content, and topic—to maximize the results of the marketing effort (Shoushtari et al., 2023). These optimization systems use AI to analyze performance metrics and adjust campaign settings automatically to boost efficiency and effectiveness throughout (Achnani, 2025).

With this, research has been conducted showing that optimizing the advertising strategies leads to better engagement rates, efficient resource use, and better campaigns results (Zieger et al., 2023). Additionally, AI has been instrumental in improving content creation, ad targeting, and campaign management, helping businesses adapt to evolving consumer behaviors and market trends

(Gao et al., 2023). The success of various forms and positions of advertising further affects consumer attention and interaction, as well as the optimization of advertising is an important part of digital marketing success (Lin, 2024).

The effectiveness of marketing activity is measured in terms of the number of clicks, click-through rates (CTR) and conversion rates. These indicators allow organizations to evaluate the effectiveness of targeting and optimization efforts and assist them in making informed decisions (Rahman and Hye, 2022). While there are some previous studies that discuss the effects of targeting and optimization separately, few studies have explored how these two factors can affect marketing performance together in an integrated algorithmic marketing context. Therefore, in this study, it can be hypothesized that combining consumer targeting characteristics and factors related to the optimization of advertising can enhance advertising performance outcomes, thus furthering the knowledge of the effectiveness of advertising algorithms in digital environments.

3. Methodology

3.1 Research Design

The design of this study is quantitative research, which examines the role of characteristics that target consumers and factors of optimization in advertising on the marketing performance outcomes in an algorithmic marketing framework. The approach used was a cross sectional since the analysis is based on one dataset taken at one specific time. With digital marketing, quantitative methods can be used to find relationships between different variables and to build empirical evidence of the effectiveness of advertising.

3.2 Data Source and Sample

Data for the study is secondary data made up of 10000 observations of advertising. The data includes demographic details like age, sex, income and location, along with the variables of advertising like ad type, ad topic and ad placement. Furthermore, it contains some

among the most important performance indicators such as clicks, click-through rate (CTR), and conversion rate. The results are both reliable and have a good basis for statistical and predictive analysis since it is a large sample size (Tawade et al.,2024).

3.3 Variable Measurement

The study defines the variables as independent and dependent. Advertising optimization factors such as ad type, ad topic, and ad placement are independent variables, as are consumer-targeting characteristics like age, gender, income, and location. The dependent variables are marketing performance outcomes, such as clicks, CTR and conversion rate. These variables have been chosen due to their significance as dimensions of the effectiveness of targeting, optimization of a campaign and the effectiveness of advertising.

3.4 Data Preparation and Analysis

The data was checked for missing values, duplicate records, and inconsistencies before analysis to ensure the quality of the data. Categorical variables were coded into numbers suitable for statistical and machine learning analysis. Descriptive statistics were used to present the results of the dataset characteristics, and correlation analysis was used to analyze the relationship between variables. These procedures set the groundwork for future predictive and inferential procedures.

3.5 Statistical and Machine Learning Techniques

Multiple linear regression analysis was used to examine the impact of the consumer-targeting and optimization factors on marketing performance outcomes to meet the objectives of the study. Furthermore, two machine learning models were created: Random Forest and Extreme Gradient Boosting (XGBoost) models, to increase the accuracy of the predictions and to determine the importance of the most influential factors affecting the advertising effectiveness. Model performance was judged based on R^2 , Root Mean Square error (RMSE) and Mean Absolute error (MAE). Further analysis of the importance of features was performed to understand the relative impact of each feature on clicks, CTR and conversion rates.

4. Results

4.1 Data Screening and Descriptive Statistics

The data set was checked for missing values, duplications, and invalid data prior to analysis. There were no missing values or duplicate records found. There were 146 observations with negative age and income values, however, and these were dropped, leaving 9,854 observations. The outcome of data screening is shown in Table 1.

Table 1. Data Screening Results

Screening Criterion	Result
Initial Observations	10,000
Missing Values	0
Duplicate Records	0
Invalid Observations Removed	146
Final Sample Size	9,854

Table 2 shows descriptive statistics for numerical variables. The mean age of the respondents was 34.24 years and mean income was 50080.04. The

average number of clicks was 5.03 and the average conversion rate and CTR were 0.202 and 0.050 respectively.

Table 2. Descriptive Statistics of Numerical Variables

Variable	Mean	SD	Minimum	Maximum
Age	34.24	14.79	0	92
Income	50,080.04	19,935.83	0	126,635.80
Clicks	5.03	2.26	0	17
Conversion Rate	0.202	0.121	0.001	0.732
CTR	0.050	0.020	0.000	0.127

The distribution of categorical variables is summarized in Table 3. As shown in Figure 1, the

sample had relatively equal distribution across the demographic and advertising categories.

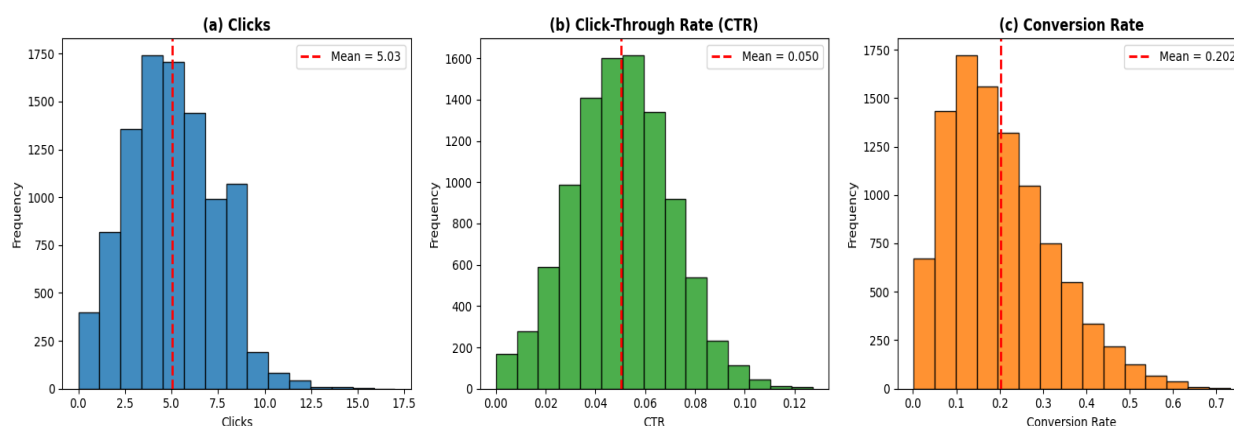
**Figure 1. Distribution of Marketing Performance Outcomes**

Figure 1(a) shows that clicks are concentrated around the mean of 5.03, (b) indicates that CTR is approximately normally distributed around 0.050, (c) reveals a positively skewed conversion rate

distribution with a mean of 0.202. Overall, the variables exhibit sufficient variability for further analysis.

Table 3. Distribution of Categorical Variables

Variable	Category	Frequency
Gender	Male	4,986
	Female	3,962
	Other	1,052
Location	Rural	3,408
	Suburban	3,307
	Urban	3,285
Ad Placement	Social media	3,340
	Search Engine	3,331
	Website	3,329

4.2 Correlation and Multicollinearity Assessment

Correlation and diagnostic of multicollinearity

were performed before regression analysis was conducted. The correlation coefficient results showed that the relationship between the independent variables was generally low. No

correlation was found which was greater than 0.80, the recommended limit. The highest observed correlations are summarized in Table 4.

Table 4. Highest Correlation Coefficients

Variables	Correlation (r)
Ad Placement (social media – Website)	-0.501
Location (Suburban – Urban)	-0.493
Gender (Male – Other)	-0.343
Ad Type (Native – Video)	-0.332
Ad Type (Native – Text)	-0.327

Multi collinearity was evaluated using a variance inflation factor (VIF) analysis. All the VIF values are below the critical value of 10 as seen in Table

5, which indicates that there is no possible severe multicollinearity in the study.

Table 5. Variance Inflation Factor (VIF) Results

Variable	VIF
Income	5.77
Age	5.26
Gender_Male	2.15
Ad Placement_social media	1.89
Ad Placement_Website	1.88
Location_Suburban	1.88
Location_Urban	1.86
Remaining Variables	< 2.00

4.3 Multiple Regression Analysis

A multiple regression model was estimated to use CTR as the dependent variable. The results found in Table 6 show that the model is not statistically significant, $F(16, 9837) = 0.93$, $p = .534$. The

overall model accounted for just 0.2% of the variance in CTR ($R^2 = 0.002$), which indicates poor explanatory power.

Table 6. Regression Results for CTR

Statistic	Value
R^2	0.002
Adjusted R^2	-0.000
F-statistic	0.930
p-value	0.534
Sample Size	9,854

The same applies to the conversion rate model, which was also found to have low explanatory power. As shown in Table 7, the model was not value of 0.002.

statistically significant, $F(16, 9837) = 0.95$, $p = .513$, with an R^2

Table 7. Regression Results for Conversion Rate

Statistic	Value
R ²	0.002
Adjusted R ²	-0.000
F-statistic	0.947
p-value	0.513
Sample Size	9,854

The regression coefficients indicated that none of the variables targeting consumers or optimizing

for better performance had significant impact on the CTR or conversion at the 5% level.

Table 8. Summary of Regression Findings

Variable Group	Significant Effect
Consumer Targeting Variables	No
Advertising Optimization Variables	No
Overall Model (CTR)	Not Significant
Overall Model (Conversion Rate)	Not Significant

4.4 Machine Learning Analysis

To investigate possible nonlinear relationships, a model based on the Random Forest technique was generated. The R² value of the model was -

0.085, which was not very good. The mean absolute error (MAE) and the root mean square error (RMSE) were 0.100 and 0.123 respectively. Table 9 shows the metrics of predictive performance.

Table 9. Random Forest Performance Metrics

Metric	Value
R ²	-0.085
MAE	0.100
RMSE	0.123

Even though the predictive accuracy is not that high, the feature importance analysis was able to tell the most important variables for the model.

Table 10 shows that as seen in Figure 2 Income and Age were the most contributing factors.

Table 10. Feature Importance Rankings

Rank	Variable	Importance (%)
1	Income	40.28
2	Age	23.38
3	Gender_Male	3.21
4	Location_Urban	3.10
5	Location_Suburban	2.95
6	Ad Placement_Website	2.94
7	Ad Type_Text	2.74
8	Ad Placement_social media	2.73
9	Ad Type_Video	2.67
10	Ad Type_Native	2.52

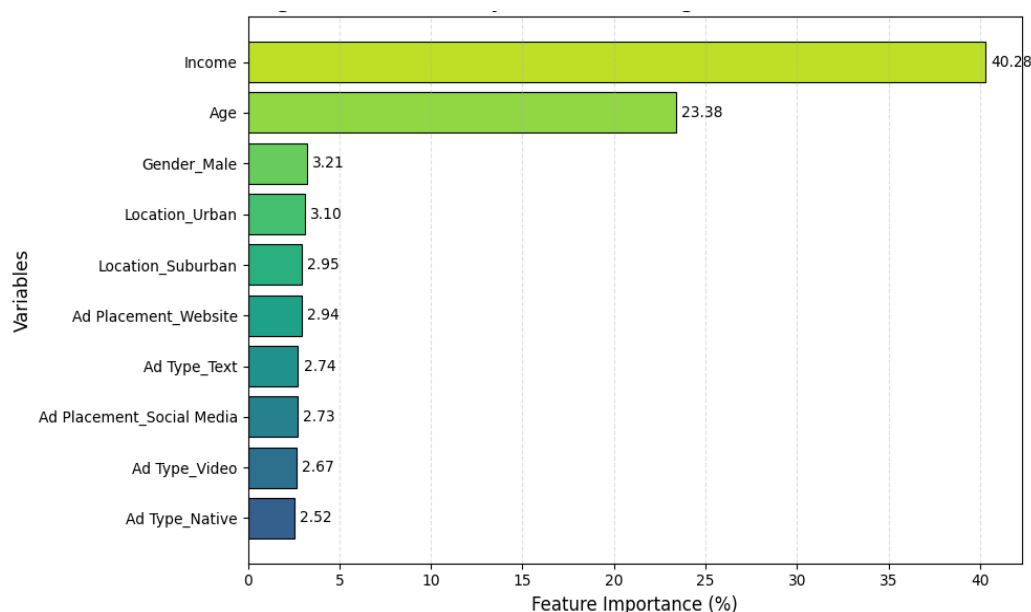


Figure 2. Feature Importance Ranking from the Random Forest Model

Figure 2 presents the relative importance of predictor variables in the Random Forest model. Income (40.28%) and age (23.38%) emerged as the most influential factors, while advertising-related variables exhibited comparatively lower importance, indicating limited contributions to predicting marketing performance outcomes.

5. Discussion

The conclusions of this research study offer significant insights into the bond between consumer-targeting characteristics and advertising optimization elements along with the marketing performance outcomes in an algorithmic marketing environment. Demographic targeting variables (age, gender, income and location) and optimization variables (ad type, ad topic and ad placement) did not significantly impact click-through rate (CTR) or conversion rate in the results found, as opposed to what was suggested in the literature. The explanatory power of both regression models was very low and the machine learning analysis showed poor predictive power. The results indicate that the variables selected account for only a small percentage of the variance in results in advertising and that consumer response to advertising is more complex in today's digital environment.

The results differ from previous studies that emphasize the effectiveness of AI-driven targeting and personalization strategies in enhancing

advertising performance. As it is suggested by the previous studies, algorithmic marketing can help organizations to segment, target, and deliver personalized content to their audience which will ultimately increase engagement and conversion (Anshari et al., 2019; Bhardwaj et al., 2024). Likewise, research has demonstrated that behavioral targeting and clickstream analytics can play a crucial part in customer segmentation and enhancing campaign performance (Sakalauskas and Kriksciuniene, 2024). But the existing results indicate that purely demographic data might not be enough to forecast the success of advertising (Michael et al., 2024). This could be due to the growth of digital advertising environments in which customer behavior isn't only shaped by more static factors like demographics.

The results also offer an interesting insight into how advertisements can be optimized. Previous studies have shown that optimizing marketing practices such as selecting ad placements, fine-tuning content, and automating campaigns boosts marketing efficiency and effectiveness (Shoushtari et al., 2023; Zieger et al., 2023). Moreover, AI-driven advertising platforms are thought to enhance the effectiveness of advertising campaigns and optimize marketing strategies through real-time adjustments and

learning from consumer behavior and campaign metrics (Achnani, 2025; Gao et al., 2023). However, the non-significant relationships found in this study suggest that some of the variables related to optimization do not have a significant influence on the outcomes of performance (Al Rafi, 2022). Instead, their value might be contingent upon the addition of other elements like consumer engagement actions, contextual relevance, algorithms on the platforms, and real-time decision-making processes.

The findings resonate with the theoretical perspective on organizational effectiveness of Information Processing Theory which posits that organizational effectiveness relies on the capability to handle complex and unpredictable information environments (Wickens and Carswell, 2021; Srinivasan and Swink, 2018). Given these variables limited predictive value, the information represented by simplified demographic and advertising configuration data might be insufficient for the explanation of consumer behavior in the context of digital advertisements. Therefore, more complex datasets, such as behavioral, transactional and contextual data, may be needed to understand the effectiveness of algorithmic marketing. Furthermore, this research builds on the growing body of literature focused on algorithmic marketing by showing that algorithms based on consumer and advertising data do not necessarily lead to better marketing results (Dilaver and Dilaver, 2024; Kozinets, 2022).

As a manager, it seems that the results suggest caution when designing digital marketing campaigns solely based on demographic segmentation and simple advertising decision configurations. While these are still useful audience segmentation factors, they seem to be not enough to project advertising effectiveness. Therefore, marketing managers should focus on developing strong capabilities in advanced analytics that leverage customer engagement patterns, behavioral data, and real-time interactions, enabling them to make better-informed decisions and optimize their campaigns for success (Upadhyay et al., 2024; Rainy, 2025). In conclusion, the research emphasizes the importance of developing a more comprehensive and data-

driven strategy for algorithmic marketing, integrating targeting and optimization tactics with additional sources of consumer information and insights generated by platforms.

6. Conclusion

In this study, the author analyzed how characteristics of consumers and the optimization factors of advertisements affect the performance of marketing in the algorithmic marketing context. The study examined the influence of demographic factors (age, gender, income and location), optimization factors (ad type, ad topic and placement) on clicks, click-through rate (CTR) and conversion rate using an existing data set of 9,854 observed ads. The results indicated that none of the consumer-targeting or advertising optimization variables was significant in explaining the differences in advertising performance outcome. In both regression and machine learning analysis, there was very weak explanatory and predictive power, indicating that the variables selected in these analyses are not enough to explain the effectiveness of advertising in today's digital world. The findings suggest that the consumer's reaction is not just dependent on pattern of consumption but also on a wide range of other factors such as platform algorithms, contextual conditions, real-time interactions, and data-driven mechanisms of personalization. The study joins a large body of work on algorithmic marketing by empirically refuting the notion that merely demographic targeting and basic campaign optimization are the two main factors to be considered when predicting performance outcomes. The results emphasize the need for incorporating behavioral, transactional and engagement data into a marketing decision making process from a practical point of view. The research highlights the importance of developing more comprehensive and intelligent marketing analytics frameworks to better harness the power of various data sources and achieve more precise targeting, more effective optimization and more successful advertisements in increasingly complicated digital ecosystems.

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