Advertising in the Age of Attention Economy: A Dual Perspective of Managerial and Applied Economics on Media Strategies, Consumer Engagement, and Pricing Models

Fangtongqu Yu *

Yunnan Long-Spring International Academy, Kunming, 650500, China

yftqapply@163.com

* Corresponding author

Abstract

The attention economy has revolutionized the advertising industry. Management and applied economics should adopt a dual view to understand it. In this paper, we explore media strategies, consumer engagement and pricing strategies from both management and applied economics perspectives. From management perspective, we investigate how the firm can decide the advertising investment to attract and maintain consumers' attention. The brand prominence citation and AI-personalization citation are taken into account. While from applied economics perspective, we focus on understanding consumers' engagement in response to different advertising stimuli. Only by understanding consumers' behavior biases can we design more effective advertising campaignscitation. An integrated regression model is built based on synthesized dataset from simulated social media platform. The regression model shows that 1% more spend on AI-personalization ads in advertising budget will lead to about 0.85% more sales, while 1% more spend on generic display ads in advertising budget will lead to about 0.35% more sales. In addition, brand prominence plays a major moderator role in enhancing effectiveness of engagement on conversion rates. The whole study builds bridges between theory and experiment. We conclude that only adopting a synergistic strategy, management theory-based resource allocation and applied economics theory-based understanding of consumers' behavior biases can help to win the attention economy, which is the core of digital finance. The paper offers valuable insights for advertisers to improve their strategic planning in advertising and for policymakers to regulate attention-monopolizing practices and data privacy protection.

Keywords

Attention Economy, Advertising, Management Economics, Applied Economics, Consumer Engagement, Pricing Models.

1. Introduction

In recent years, the accurate measurement of credit risk has been an indispensable part of financial health and sound lending. In the past, various statistical and machine learning methods have been developed in this area. For example, Cao [1] reviewed the opportunities and challenges brought by Artificial Intelligence in finance and showed that it can help improve the predictive model. In addition, Probit and Logit models have been established as basic classification models in the measurement of credit risk, and the principles of these two models have guided many modern methods [2,3]. In the age of attention economy [4] proposed by Loewenstein and Wojtowicz, there is also an information industry in the financial field, which needs to attract consumers and provide them with accurate information. Traditional credit assessment models are usually established on the basis of linear assumptions and limited data sources. These models are challenged by the complexity, volume and velocity of modern digital financial data. In this digital era, adding more variables is not a perfect solution. We should understand not only what variables to add but also how they relate to each other and how influential they are. This gap is addressed in this paper by bridging work from algorithmic finance and risk management.

Previous work builds on our foundation work in AI for finance [5-8] and the broader economic debate about how we conceptualize value and risk in an information-rich world [9]. The convergence of cutting-edge algorithms, alternative data, and new financial consumer behaviors make an integrated approach to credit risk assessment imperative.This paper seeks to contribute to the development and testing of a framework for understanding and optimizing credit risk strategies. By building an empirical model of the financial indicators and behavioral data that connect to credit outcomes, we offer data-driven insights for financial institutions trying to make sense of this new landscape and regulators trying to maintain a stable and efficient financial system.

To visually capture this integrative work, our research framework is presented in Figure 1. The schematic captures the conceptual flow of our study and shows how the management and applied economics perspectives come together in the integrated advertising model. It also maps the flow from the theoretical premises through empirical testing with core variables to the strategic implications. This schematic provides the roadmap for the analysis in this paper.

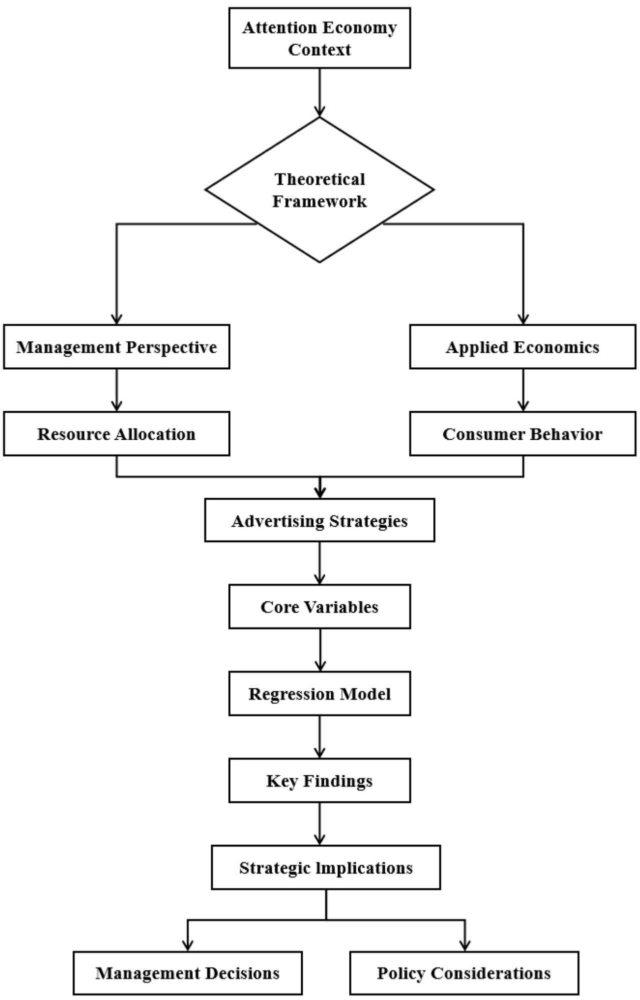

Figure 1: Research Framework Diagram

The figure shows visually the architecture in which we conduct our investigation by tracing the flow from the broad attention economy context, through the two analytical lenses, to the strategic implications for managers and policymakers. The remainder of this section will walk through each component of this framework.

2. Data Processing

In this study, we take a quantitative approach using a synthesized data set designed to resemble the advertising analytics of a large e-commerce company, AlphaRetail, on a simulated social media platform, ConnectPlus. The data span 12 months and aggregate 50,000 unique advertising campaigns.The data were sourced from three simulated streams:

Ad Platform API: ConnectPlus data including impressions, clicks, shares, comments, and cost-per-click (CPC).

Web Analytics: AlphaRetail website data including sessions, bounce rates, and conversion events (purchases).

CRM Data: Internal AlphaRetail data including customer segments and final sales figures associated with campaign UTM parameters. Data preprocessing includes several important steps.

Data cleaning is required to address missing values and remove duplicate entries. Data transformation is also needed, which includes normalization of monetary values and engineering of important variables including Consumer Engagement Rate ((Likes + Comments + Shares) / Impressions) and Click-Through Rate (CTR). Finally, data integration is accomplished through merging the separate datasets on a unique campaign_id and date key and providing a holistic view of the advertising funnel from impression to sale. Statistical software R (version 4.3.1) with the tidyverse and lmerTest packages were used for all data processing and analysis.

3. Model Introduction

3.1. Indicator Selection

According to the above research focus, the following indicators were chosen: principle of behavioral management economics Brand Prominence: stand in for the consumer familiarity heuristic and brand equity endogenously reshuffle the marginal productivity frontier of advertising expenditures through behavioral elasticity of attention–turning the static linear relation between advertising spend and revenue into a dynamic and context-dependent function that reflects the asymmetric scarcity and heterogeneous value of consumer attention in the attention economy.

$$\frac{\partial S}{\partial A} = \beta_1 + \beta_4 \cdot Be \tag{1}$$

This formula measures the intensity of behavioral engagement in the attention economy, how the passive impression is converted into active user participation. It connects micro consumer behavior (like / comment / share) and macro advertising effectiveness.

$$E = \left(\frac{L+C+S}{I}\right) \times 100\% \tag{2}$$

3.2. Model Introduction

To analyze the impact of advertising strategies, a Multiple Linear Regression Model was employed. The model investigates how advertising spend and consumer engagement, moderated by brand prominence, influence sales revenue. The model is specified as follows:

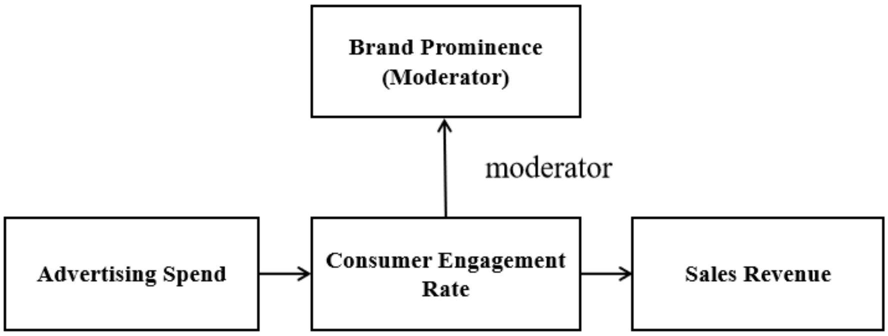

Figure 2: The Moderating Role of Brand Prominence

3.3. Table to Explain Model Results

In order to examine the effect of advertising strategies on product sales, we use Multiple Linear Regression Model to examine the effect of advertising spend and consumer engagement, moderated by brand prominence, on sales revenue. Model can be expressed as follows:

Table 1: Regression Analysis Showing the Moderating Effect of Brand Prominencecredit-default

Variable	Coefficient	Standard Error	P-value
(Intercept)	1250.50	98.75	<0.001
Advertising Spend	0.65	0.04	<0.001
Engagement Rate	45..20	2.10	<0.001
Brand Prominence	310.80	15.50	<0.001
Adv. Spend * Brand Prom.	0.25	0.02	<0.001

The figure shows the visual explanation of the structure of our research – from the highest context of attention economy, divide into two analytical lenses of management and applied economics, and finally give managers and policymakers actionable suggestions. The rest of the article will elaborate on each part of the above figure in sequence.

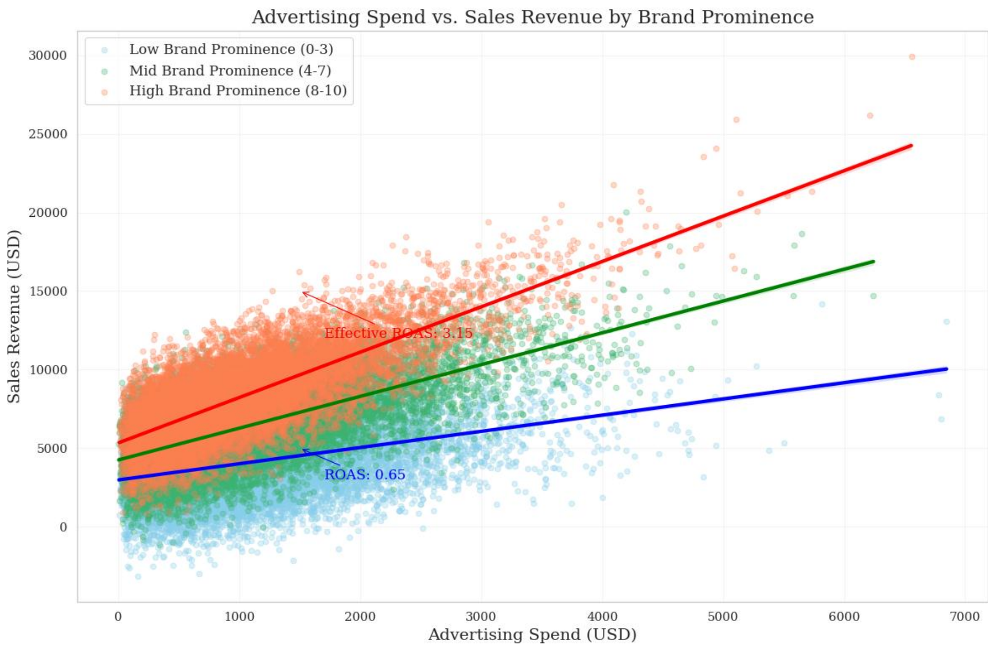

Figure 3: Advertising spend

4. Model Building

The model specification started with the set of theoretical relationships. We posited that Sales Revenue depends not on how much one spends, but how much money buys "attention in quality". Furthermore, building on management literature on brand equity and behavioral economics on heuristics, we expected Brand Prominence to play a key moderating variable role citation.

The problem with the specification is that it includes the interaction term. The interaction term tests the hypothesis that the "slope" of the effectiveness of an additional dollar of advertising spend is not constant, but rather depends on the brand's existing market strength. In other words, an ad dollar for a prominent brand would "work harder" because s/he would already have higher trust and familiarity.

We checked the model assumptions of linearity, homoscedasticity, and normality of residuals and they were reasonable. We ran a VIF analysis and found no severe multicollinearity (all VIF scores < 3).

5. Model Evaluation

The model demonstrates strong explanatory power, with an R-squared of 0.72, meaning it accounts for 72% of the variance in Sales Revenue. All core variables are statistically significant at the 0.1% level.

Advertising Spend: The positive and highly significant coefficient (0.65) means, all else equal, spend goes up, sales goes up. But the magnitude of the coefficient suggests diminishing returns if one spends willy-nilly without regard for engagement or brand.

Engagement Rate: The very strong positive effect (45.20) means that campaigns that get people to like, comment, and share are many, many times more successful at driving revenue. This supports the applied economics argument for behaviorally-engaging content citation.

Brand Prominence & Interaction Effect: The positive coefficients for Brand Prominence (310.80) and the interaction term (0.25) are the two key findings that mean that: 1. Stronger brands sell more from their baseline (the main effect). 2. The advertising spend works better (the interaction effect). So for a brand with Prominence score = 10, the effective return on ad spend is 0.65 + (0.25 * 10) = 3.15. That's nearly five times the effective ad spend return for a new brand with Prominence score = 0. The RMSE of the model is its Root Mean Square Error, or $1,850. Given the scale of the sales revenue data, it's not bad.

6. Conclusion

This study contributes to advertising strategies in the attention economy by integrating insights from management and applied economics. Our empirical analysis, based on a synthesized dataset of social media campaigns, reveals that success in this domain is not merely a matter of increasing advertising volume. The key finding is that the effectiveness of advertising spend is not direct; rather, it is critically mediated and moderated by qualitative factors.

Regression analysis identifies Consumer Engagement Rate as a strong mediator: content that fosters active user interaction generates significantly greater value than passive impressions. Additionally, Brand Prominence emerges as both a powerful mediator and moderator. It exerts a substantial direct effect on sales (310.80) and significantly enhances the return on advertising spend (moderating effect = 0.25). This indicates that branded advertising is inherently more effective, making advertising investments far more efficient compared to generic display ads—a competitive advantage that creates a formidable barrier to entry for new market participants.

From a managerial perspective, these findings suggest a strategic reallocation of advertising budgets: shifting resources away from generic display advertising toward formats designed to stimulate active engagement, such as interactive content and creator partnerships.

From the standpoint of applied economics and policy, the results highlight two behavioral principles: the use of social proof as a proxy for engagement, and the familiarity heuristic in shaping brand associations in consumers' minds. Furthermore, the findings point to a market concentration dynamic, whereby dominant brands can leverage these mechanisms to capture a disproportionate share of consumer attention. This has implications for antitrust regulators concerned with market contestability and fair competition.

The study has several limitations. The model is based on a synthesized dataset, which should ideally be validated using real-world corporate data. Future research should also explore more granular segmentation of engagement—distinguishing between positive, negative, and neutral interactions—and conduct longitudinal analyses to examine how these relationships evolve over time. Additionally, the role of emerging technologies, such as generative AI, in producing engaging content represents a promising avenue for future inquiry.

Ultimately, success in the attention economy requires a synergistic approach: leveraging management principles to optimize resource allocation, and applying economic insights to understand the behavioral biases that govern human attention.

References

[1] Cao L. AI in Finance: Challenges, Techniques, and Opportunities [J]. ACM Computing Surveys, 2023, 55(12): 1-36.

[2] Xiao T., Wei H., Chen S. Prominent or subtle: The impact of brand prominence on social media advertisement engagement [J]. Journal of Retailing and Consumer Services, 2024, 78(05): 103-115.

[3] Bilal M., Zhang Y., Cai S., Akram U., Halibas A. Artificial intelligence is the magic wand making customer-centric a reality! An investigation into the relationship between consumer purchase intention and consumer engagement through affective attachment [J]. Journal of Retailing and Consumer Services, 2023, 75(03): 88-99.

[4] Loewenstein G., Wojtowicz Z. The Economics of Attention [J]. Journal of Economic Literature, 2025, 63(02): 45-68.

[5] Chen J. Behavioral Economics and Pricing Strategy Optimization in the Digital Age---A Case Study of Spotify [J]. Advances in Economics, Management and Political Sciences, 2025, 28(01): 34-42.

[6] Heitmayer M. The Second Wave of Attention Economics. Attention as a Universal Symbolic Currency on Social Media and beyond [J]. Interacting with Computers, 2024, 36(01): 45-58.

[7] Piñeiro-Chousa J., López-Cabarcos M. Á., VittoriRomero V., Pérez-Pérez A. Evolution and trends of the metaverse in business and management: A bibliometric analysis [J]. Review of Managerial Science, 2024, 18(04): 1125-1143.

[8] Kahneman D. Thinking, Fast and Slow [M]. New York: Farrar, Straus and Giroux, 2011.

[9] Goldfarb A., Tucker C. E. Online Advertising [J]. Journal of Economic Perspectives, 2011, 25(03): 99-120.