

Confirmation Bias and AI Features: How They Influence Consumer Decisions in Apple Purchase

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Abstract. This study is to determine how the presence of artificial intelligence in smartphones affects the decisions of consumers by taking into consideration confirmation bias and the availability heuristic. A method was used for an experiment; this method involved an experimental group subjected to information about Apple's AI features and a control group not exposed to this information. The surveys were conducted by using both Google Form Survey and Wenjuanxing, which were distributed to different cultural backgrounds in China. The data analysis manifest that the treatment group purchased Apple products 2.61 times more than the control group, demonstrating the extreme power of the cognitive aspects in guiding purchasing behavior. The research also showed that consumers are more likely to take on and reinforce beliefs already held instead of accepting something new if they are influenced by the confirmation bias. This research consequently reveals the practical aspects of understanding cognitive biases in marketing practices with respect to impulses and needs of consumers.

Keywords: Confirmation Bias, Artificial Intelligence in Marketing, Availability Heuristic, Consumer Decision-Making

1. Introduction

With the development of artificial intelligence (AI) in the recent years, the technology sector of consumer goods has experienced a great effect on consumer behavior. The incorporation of artificial intelligence (AI) features into smartphones is not only becoming an essential decision point for purchase choices but is also indicative of customers' proclivity to more advanced and discerning mobile devices. The present study aims to present the contribution of AI features to consumer's decision-making processes in the smartphone market with the regard to confirmation bias and availability heuristic.

Smartphone industry has among the most aggressive competition levels, and brands increasingly compete for consumer preferences through continuous improvement. Past research has underscored the relevance of multi-faceted variables, for instance, brand loyalty, product price sensitivity, and technology innovation, in informing purchasing decisions [1]. However, there is lack of studies which explain the influence of cognitive biases regarding confirmation and availability in consumer choice processes. In this information age, where it is just a click away for anyone to search and frame a bias based on these two factors, namely confirmation bias and availability heuristic bias are the main obstacles for a consumer in the making of the digital purchases [2,3].

The artificial intelligence features, which are becoming more and more essential and attractive according to consumers, are favored in this research. Benefits of artificial intelligence, like recommendation engines, voice assistants, and the sophisticated camera controls, augment the user experience and set apart products in the competition realm. A report by Canalys [4] states that the Chinese consumers particularly value AI features, as among them 27% would consider switching their brand just to access new functionalities based on AI. AI is a prime influencer of consumer choice and brand loyalty, as this trend shows.

Consumers are apt to be subjected to confirmation bias because of it being responsible for how information is processed and decisions are made. Confirmation bias refers to a tendency of consumers to look for the evidence supporting their ideas, even disregarding the contrary information. This proclivity can distort impressions, reproduce preferences, and is, therefore, an effective marketing and ad tool [2]. Whenever there is no incoming information, consumers may maintain their previous positions, but when new, forceful information comes in, for example, intelligent features of AI, it will definitely affect consumer behavior.

For this reason, we explore the impact of AI features on the decision of mobile phone purchase by an experiment that the participants classify into two groups corresponding to either an experimental or control group receiving the information on the AI features. We surveyed the questionnaire data, targeting the Chinese students using Google Form Survey and Wenjuanxing. We used this method because we have different regional backgrounds. Our questionnaire design aimed to grasp factors that perhaps could influence mobile phone purchase choices, such as satisfaction, income level, educational background, and people's gender.

We employed a rigorous research methodology to obtain findings, which will have reliability and validity. The question comprehends variables that were possible to be a factor in purchase decisions were put together for the survey. In order to minimize selection bias, participants were randomly assigned to either the experimental group or the control group. Data collection was scheduled on the weekly basis to ensure that the sample included a wide variety of data.

For the purpose of analysis, we used statical tools to test the difference between the group's answers. Descriptive statistics used to describe the data were utilized in the study. For instance, t-tests and regression analysis were done to determine whether the differences observed between groups were statistically significant. The primary variable of interest was whether the likelihood of purchasing Apple products, which was statistically compared between experimental and control groups.

Our research revealed that the test group, armed with information about ML-related features, was 2.61 times more likely to choose Apple products than the control group. This means that the existence of state-of-the-art AI capabilities, which are, to a large extent, based on ML algorithms, greatly interfere with the patterns of consumer behavior. Besides that, although the two groups exhibited parity in terms of satisfaction level, income, education, and gender, the treatment group showed a higher degree of purchase among its members, as well as an increased attention to Apple's

products. These findings reinforce the point that AI features have the capacity to disrupt and control consumer behavior decisions and are governed by the existence of cognitive biases [5].

2. Literature review

2.1. Importance of confirmation bias

Confirmation bias plays an important role in shaping consumer behavior and choices, supporting many of the underlying reasons that are seen as irrational decisions. In psychological literature, it is usually defined as seeking or interpreting information in a way that is biased towards current views, expectations, or hypotheses [6]. It can be described as people's tendency to frequently seek, evaluate, and generate new evidence to validate their pre-existing views [7]. People who experience confirmation bias cannot guarantee that logic is dialectical. When analyzing a commodity or a social event, they tend to spend more time proving their inherent views on specific things or items. Therefore, this may seriously affect the prediction of consumer choices by enterprises and create consumption traps for consumers themselves.

For instance, an investor who performs well in the stock market can use a small amount of capital to achieve good returns, so he believes in his own ideas on how to invest. When making new investment choices, he tends to accept financial information that supports his ideas and ignores some potentially useful information. This makes it impossible for consumers to objectively evaluate products based on new information provided by companies when they have pre-existing opinions. Moreover, people use certain channels or websites to obtain information and make biased conclusions and further consumption choices through biased reporting and description of products. For example, social media is the main way of disseminating information in today's era, and some attractive headlines or simple statements about special events or products can quickly take advantage of people's confirmation bias to spread widely.

People rarely check the credibility of information sources and are more receptive to similar information promotions. Because an infinite amount of information may affect search engine preferences for search [8]. Titles like 'APPLE AI leads the next decade' can encourage search engines to push more relevant content to interested users. This selective information processing can lead to biases in the perception of product quality or value, so our experiment mainly focuses on the variable of AI information to study the specific impact of confirmation bias.

2.2. Marketing & branding

Enterprises use confirmation bias in the marketing field to promote procurement decisions. Studying this psychological barrier can better help creators of marketing content use advertising to attract consumers. A study elucidates the cognitive problem of confirmation bias, which refers to how beliefs and expectations can influence the selection and evaluation of evidence in different ways to enhance people's self-awareness [9]. If our model demonstrates that confirmation bias does have an impact on the decision to purchase a new Apple, then businesses can use confirmation bias as a marketing tool through advertising to establish a better corporate image and attract more types of consumers. For example, Apple can use AI advertising to leave a deep impression on people with disabilities, and new features can better assist their daily lives or generate positive impact in health services.

The new feature can also attract more people who are not interested in purchasing through creative advertising introductions. This plays a crucial role in improving the sales strategy of

enterprises. In addition, Unethical advertising activities that use false advertising and customer privacy can have a negative impact on society. Therefore, enterprises need to realize that the effectiveness of advertising must be based on fairness and authenticity rather than unethical false advertising to increase sales.

2.3. The main difference between availability heuristic and confirmation bias

The availability heuristic bias and confirmation bias have different impacts on consumer behavior and decision-making. In fact, availability heuristics are a cognitive bias where you make decisions based on an example, information, or recent experience, even if it may not be the best example for you to make a decision [10]. For example, consumers' AI recall encountering many difficulties and inconveniences when using AI. Although AI has many functions that can be applied to daily life, they find it difficult to recall relevant information to promote their purchases. The addition of AI information can observe different effects of two biases on consumers. Testers with high satisfaction levels with existing Apples may be more susceptible to heuristic bias when purchasing new Apples, as they recall relevant advantages to promote their purchasing desire.

On the other hand, testers who have experienced confirmation bias have a very low level of satisfaction with the existing Apple, which means that even if the new features are good, they will not change their previous views. In general, availability heuristic bias is about the impact of recall difficulty on frequency judgment, while confirmation bias is about selective information processing that is consistent with existing beliefs [11].

2.4. The importance of selected variables

Adding variables such as age, gender, income, education level, and WTP as explanatory variables in the experiment can better highlight the impact of intervention or treatment on whether to purchase an Apple in the experimental group, avoiding additional effects that may be caused by other variables. For example, age may affect a person's perception of a product or service, while income can affect their willingness to pay. Therefore, including these explanatory variables allows our experiment to control for potential confounding factors that may distort the results. Different age groups have their own specific purchasing behaviors and attitudes towards products and services. The baby boomer generation, known for brand loyalty, often pursues quality and reliability. However, the digital native Generation Z (1997-2012), born in the era of technological development, prioritizes authenticity and social responsibility [12]. And men and women often exhibit different consumer behavior patterns [13].

Gender as our independent variable can distinguish the degree of preference for electronic products between different genders to eliminate potential influence. For example, men prioritize product features and functionality, while women prioritize factors such as product aesthetics and customer reviews [12]. So perhaps our treatment information AI is more attractive to men. Moreover, higher income levels typically mean greater purchasing power, enabling consumers to accept more expensive goods and services. The price of a new Apple in China is around 10000 yuan, which far exceeds the average monthly salary in many provinces. Consumers with different incomes play an important role in determining the impact of bias on purchasing choices.

In addition, the difference in educational level leads to consumers having different attitudes towards the updates of technology products. People with higher levels of education are more willing to study how new features can assist in various aspects [12]. Therefore, we use the results of these

variables in the survey questionnaire to offset some potential impacts and highlight the importance of AI functionality.

2.5. Research gap

While existing studies have extensively explored cognitive biases in various contexts, there is a relative lack of focused research on how these biases specifically influence the choice between mobile phone brands. Most studies tend to generalize across product categories, leaving a gap in understanding the unique dynamics of high-involvement products like smartphones. In addition, with the rise of digital marketing, it may be crucial to understand how online content (such as ads, comments, social media) exploits these cognitive biases. The potential manipulation of consumer choices through these biases remains an area that can benefit from more empirical research, especially in the context of digital platforms.

3. Methodology

3.1. Survey and sample

This study employs an experimental design to investigate how the application of confirmation bias and availability heuristics, along with the provision of reviews and information about previous Apple products, influences the likelihood of purchasing Apple devices. Participants are randomly assigned to either a treatment group, which receives additional details about the functions and reviews of past Apple phones, or a control group, which does not receive this information. The objective is to determine whether exposure to Apple-related information significantly affects participants' purchasing decisions.

The primary questions in our questionnaire include: After reviewing the information on Apple, would you change your consumption choices? Are you satisfied with your current mobile phone brand? Will you purchase a new iPhone after Apple's launch event due to its upcoming AI features? If so, what is your willingness to pay? The first question aims to assess the effectiveness of our intervention (providing participants with reviews of previous Apple products) in influencing consumption choices. Additionally, the second and third questions demonstrate the application of our theoretical framework. Specifically, by analyzing participants' satisfaction with their current mobile phone choices, we can, if significant differences emerge between the experimental and control groups, interpret participants' pre-existing beliefs about switching mobile phones in light of relevant theory. The third question supports the proposition that purchasing decisions often require incentives, particularly in this simulated purchasing context, which is less immediate than real-world environments.

Table 1. Statistics summary

Variables	Observation	Mean	Std.dev	Min	Max
Panel A: Control Group					
Launch	129	1.6	0.5	1	2
AI	129	0.4	0.5	0	1
WTP	129	6965.1	2087.2	3000	15000
Satisfaction	129	2.6	1.2	1	5
Income	129	2.4	0.9	1	4
Education	129	3.2	0.8	1	5
Gender	129	0.6	0.5	0	1
Panel B: Treatment Group					
Launch	129	1.4	0.5	1	2
AI	129	0.7	0.5	0	1
WTP	129	7450.4	2193.8	1000	15000
Satisfaction	129	2.5	1.1	1	5
Income	129	2.3	0.9	1	4
Education	129	3.1	0.8	1	5
Gender	129	0.6	0.5	0	1

A total of 258 participants are recruited and evenly distributed into the treatment (n=129) and control (n=129) groups. Data is collected through a structured questionnaire posted on platforms Wenjuanxing and Google Forms. Wenjuanxing is a leading online survey tool in China, frequently used by academic researchers, government organizations, and businesses for market research. Its reputation is well-established, as it has been referenced in many studies from Chinese academic institutions and published in peer-reviewed journals, boosting its credibility in the research world. Additionally, we used Google Forms to create and share our survey with friends and university students. The reason for using both Wenjuanxing and Google Forms was to reduce sample selection bias by reaching different groups. Wenjuanxing caters mostly to Chinese users, providing access to a large sample of respondents from a Chinese-speaking background. In contrast, Google Forms is widely used worldwide, especially in English-speaking regions, allowing us to gather responses from a variety of cultural backgrounds.

By leveraging both platforms, the study ensures a diverse sample, capturing input from various cultural contexts, which improves the generalizability of our results. Furthermore, both tools allow for easy export of data into Excel, which streamlines the data analysis process. The survey measured key factors such as participants' willingness to pay, interest in Apple's AI features, and satisfaction with their current mobile devices, along with demographic information.

3.2. Variables

The dependent variable is participants' consumption choices for APPLE given its AI function

The key independent variable is a treatment dummy meaning that whether participants receive reviews and information about previous APPLE products (1 = Yes, 0 = No)

By including additional control variables such as age, gender, income, education level, and willingness to pay as explanatory factors in the experiment, the effect of the intervention or treatment on the decision to purchase an Apple device in the experimental group can be more clearly isolated. For example, age may affect a person's perception of a product or service, while income can affect their willingness to pay. Therefore, including these explanatory variables allows our experiment to control for potential confounding factors that may distort the results. Different age groups have their own specific purchasing behaviors and attitudes towards products and services. The baby boomer generation, known for brand loyalty, often pursues quality and reliability.

However, the digital native Generation Z (1997-2012), born in the era of technological development, prioritizes authenticity and social responsibility [12]. And men and women often exhibit different consumer behavior patterns [13]. Gender as our independent variable can distinguish the degree of preference for electronic products between different genders to eliminate potential influence. For example, men prioritize product features and functionality, while women prioritize factors such as product aesthetics and customer reviews [12].

So perhaps our treatment information AI is more attractive to men. Moreover, higher income levels typically mean greater purchasing power, enabling consumers to accept more expensive goods and services. The price of a new Apple in China is around 10000 yuan, which far exceeds the average monthly salary in many provinces. Consumers with different incomes play an important role in determining the impact of bias on purchasing choices. In addition, the difference in educational level leads to consumers having different attitudes towards the updates of technology products. People with higher levels of education are more willing to study how new features can assist in various aspects [12]. Therefore, we use the results of these variables in the survey questionnaire to offset some potential impacts and highlight the importance of AI functionality.

Table 1 provides the summary statistics for both the treatment and control groups. The variables assessed include Launch, reflecting participants' awareness and attention to APPLE's product launch (1 = No interest, 2 = Interested). AI measures the likelihood of participants purchasing the product based on its new AI functionality (binary variable: 0 = No, 1 = Yes). Willingness to Pay (WTP) captures the amount participants are willing to pay for the product, measured in CNY. Satisfaction reflects participants' contentment with their current mobile devices, ranging from 1 (very dissatisfied) to 5 (very satisfied). Income denotes monthly income levels, with higher values corresponding to higher income brackets (1 = Below 5,000 CNY, 5 = Above 20,000 CNY). Education is measured on a scale from 1 (Less than high school) to 5 (Doctoral degree). Gender is measured as a binary variable (0 = Female, 1 = Male).

The treatment group demonstrates a higher mean value for AI (mean = 0.7) compared to the control group (mean = 0.4), suggesting a stronger likelihood of purchase based on AI exposure. Likewise, the treatment group exhibits a higher mean on the variable WTP (7450.4 CNY) than that of the control group (6965.1 CNY). Based on our observations of the summary statistics, we have similar means across variables satisfaction level, income, and education, indicating no significant differences across these factors.

3.3. Model specification

We utilized logistic and probit regression models to assess how likely participants are to purchase Apple devices given its AI functions after being exposed to information about APPLE. Logistic regression estimates the odds of making a purchase based on the treatment, while probit regression models the probability of purchasing using the normal distribution. These methods are commonly used in research to analyze binary outcomes. For example, Peng et al. [14] emphasize that logistic

regression is highly appropriate for analyzing binary outcomes by exploring the relationship between multiple factors and a binary response. Similarly, Wooldridge [15] explains that probit models are useful for studying decisions like whether a person seeks medical care, based on factors such as income, education, and insurance.

We estimate the model as follows.

$$y = \beta_1 T + \beta_2 X + \varepsilon \quad (1)$$

Where y is dependent variable, T is treatment, X is the vector of controls including age, gender, education, income, willingness to pay, launch, and satisfaction. ε is error term. β_1 is the coefficient of treatment to be estimated, and β_2 is the vector of coefficients of controls.

3.4. Results

Table 2 presents the results from both the logistic and probit regressions, which examine the effect of the treatment on participants' consumption choices for Apple products, given prior information. In column (1) using logistic model, the coefficient for Treatment is 0.961, with a p-value less than 0.001. Therefore, there is sufficient evidence to reject the null hypothesis that providing reviews and information about Apple's functions does not influence participants' purchasing decisions.

Table 2. Main model

Dependent variable: Participants' consumption choices for APPLE given its AI function		
	Logistic	Probit
Treatment	0.961*** (-0.29)	0.583*** (-0.174)
Constant	-0.183 (-1.024)	-0.062 (-0.618)
McFadden's R-squared	0.04	0.039
Observations	258	258

Notes: Standard errors in parentheses; *** P < 0.01, ** P < 0.05, * P < 0.1

To interpret the logistic model results, data transformations are necessary. Since the analysis is performed in R, which provides log-odds coefficients for the logistic model, the exponential of the coefficient is calculated, yielding a value of approximately 2.614. This suggests that the probability of participants making a purchase increases by 2.614 times when they are provided with reviews of previous Apple products.

Similarly, column (2) using probit model, applying the same procedure results in a coefficient of 1.791. This indicates that the probability of participants choosing to purchase Apple products increases by 1.791 times when they are given reviews of previous Apple functions.

We use both probit and logistic models to conduct robustness checks and sensitivity analyses of our experimental results. According to the hypothesis, if the results differ significantly between the two models, it may indicate that the choice of model influences the interpretation, necessitating further investigation into the reasons for the divergence. Fortunately, the data in both models yield similar outcomes, suggesting that our conclusions remain consistent and are not affected by model selection. Additionally, since both models produce comparable coefficients and significance levels,

the results appear stable and not driven by any specific distributional assumptions. This strengthens confidence in the findings.

Both the logistic and probit models demonstrate relatively low McFadden R-squared values (0.04 for the logistic model and 0.039 for the probit model). While these values indicate that the models do not explain a large proportion of the variance, this is typical for models predicting binary outcomes such as purchase decisions.

Table 3. Expanded model

Dependent variable: Participants' consumption choices for APPLE given its AI function		
Variables	Logistic	Probit
Treatment	0.96*** (-0.29)	0.58*** (-0.17)
Age	-0.04 (-0.03)	-0.02 (-0.02)
Gender1	-0.27 (-0.29)	-0.16 (-0.17)
Education	0.09 (-0.18)	0.06 (-0.11)
Income	0.03 (-0.18)	0.007 (-0.11)
WTP	0.0002** (-0.0001)	0.0001** (-0.00004)
Launch2	-0.944*** (-0.28)	-0.578*** (-0.17)
Satisfaction2	-0.35 (-0.40)	-0.21 (-0.24)
Satisfaction3	-0.62 (-0.42)	-0.38 (-0.25)
Satisfaction4	-0.26 (-0.5)	-0.17 (-0.3)
Satisfaction5	0.43 (-0.60)	0.27 (-0.36)
Constant	-0.1 (-0.94)	-0.009 (-0.57)
Observations	258	258

Notes: Standard errors in parentheses; *** P < 0.01, ** P < 0.05, * P < 0.1

We further consider adding more control variables in our model to reduce the potential biases conducted by residuals. Table 3 is us expand model which include control variables such as Age, Gender, Education Level, Income, Willingness to Pay (WTP), Launch, and Satisfaction This model helps isolate the treatment effect and control for potential confounding variables, ensuring that other factors do not distort the results. This approach also improves the understanding of demographic and

behavioral influences on purchasing decisions, offering deeper insights into the factors influencing participants' choices.

Column (1) shows that Willingness to Pay appears as a significant predictor of Apple purchases given AI function considering that p-value is less than the significance level 0.05, with a coefficient of 0.0002 in the logistic model. After performing exponentiation, the result is 1.0002, indicating that participants who are willing to pay more are significantly more likely to purchase an Apple product. This finding is same as probit model shown in column (2) that variable WTP with the coefficient of 0.0001 in table and an exponentiated value of 1.0001 support the positive effect consumption listed in the logistic table.

Column (1) also shows a significant negative effect for the Launch variable in the logistic model, with a coefficient of -0.944 and p-value less than the significance level 0.05. After exponentiation, the result is 0.389, suggesting that participants who paid attention to Apple's product launch are less likely to make a purchase. Similarly, column (2) reports a negative coefficient of -0.578 which exponentiates to 0.561 with a p-value less than the significance level in the probit model, reinforcing this finding.

Other demographic variables, such as Age, Gender, Income, and Education, do not show statistically significant effects in either model, suggesting they do not substantially influence the likelihood of purchasing Apple products based on the treatment.

Although Satisfaction Level does not emerge as a significant variable, patterns can be observed. In the logistic model (column 1), the coefficients for satisfaction levels 2 through 5, after exponentiation, are 0.70, 0.54, 0.77, and 1.54, respectively. In column (2), the probit model shows a similar pattern, with exponentiated coefficients of 0.81, 0.68, 0.84, and 1.31. For instance, in the logistic model, the coefficient of 0.70 suggests that the likelihood of purchasing increases when satisfaction rises from level 1 to 2, by automatically setting satisfaction level 1 as the baseline. However, the coefficient for satisfaction level 3 (0.54) indicates a decrease in purchasing likelihood compared to level 2. These results align with the theoretical frameworks of confirmation bias and availability heuristics that we deliver deeper in the conclusion section.

4. Conclusion

Through the aforementioned experiments and research, we have reached conclusions that may differ from those of traditional economic studies. Firstly, the experimental group exposed to information about Apple's AI capabilities is significantly more likely (2.61 times) to purchase Apple products. This indicates that innovative features like AI significantly influence consumer behavior.

Secondly The study finds that age negatively impacts purchase decisions, with younger individuals being more inclined to purchase Apple products. This may be because young consumers have a higher acceptance of new technology.

Thirdly Willingness to pay and attention to Apple's launch events are positive predictors of purchase decisions. This highlights the high level of interest consumers have in product features and marketing activities.

Fourthly Confirmation bias plays a role among participants with satisfaction levels 1-2, as these individuals are already dissatisfied and are considering alternative mobile phone brands. When presented with new information about APPLE 's AI function, they may be more inclined to switch to APPLE, as this aligns with their pre - existing negative feelings towards their current brand and supports their desire for change. For participants with satisfaction levels 4-5. Their decision to switch to APPLE may be influenced by the availability heuristic. The new information about the Apple and its AI functionality becomes readily accessible in their minds, making it easier for them to

justify the switch based on recent exposure to positive features of APPLE rather than a deep dissatisfaction with their current device.

Finally Exploring the Impact of Gender, Education, and Income on Willingness to Pay: We find that these factors do not significantly influence purchase decisions. This suggests that in the context of smartphone purchases, psychological factors and personal preferences may be more important than traditional economic variables.

We have found that combining confirmation bias and availability heuristics in the consumer decision-making process has profound implications for marketing strategy. By leveraging these insights, mobile phone companies can develop marketing campaigns that resonate more authentically with their target audience.

In terms of consumer personalization, companies can tailor marketing messages to align with consumer preferences and beliefs, creating a sense of personal connection. This approach is consistent with the theory of confirmation bias—individuals are more likely to engage with information that confirms their pre-existing notions.

in terms of Content Targeting, companies analyze consumer data to identify their spending patterns and preferences, thereby creating content that directly appeals to these areas. This strategy uses the availability heuristic by making relevant information readily accessible, thus more likely to influence the consumer decision-making process [16].

in terms of Strengthening Brand Loyalty, by providing consumers with information that supports their brand beliefs, businesses can strengthen brand loyalty. This is particularly effective for consumers with high satisfaction levels, as it confirms and reinforces their positive views of the brand.

in terms of social Media Engagement, on platforms where consumers frequently encounter brand information, businesses can foster real-time interaction, providing a sense of immediate gratification and community. This engagement not only reinforces consumers' existing choices but also creates new touchpoints for brand promotion [17].

By strategically applying these behavioral economic theories to develop better marketing strategies, companies can enhance their appeal, establish stronger relationships with consumers, and drive sales in a more targeted and effective manner.

For consumers, the findings of this study also provide insights into how to make more rational purchase decisions. We suggest that consumers consider the following when making purchasing choices.

First of all, consumers should be aware that they may be influenced by the availability heuristic and confirmation bias during the decision-making process. Understanding the existence of these psychological phenomena is the first step in avoiding their influence on decisions [6].

Furthermore, to overcome confirmation bias, consumers should actively seek information that contradicts their pre-existing views when evaluating products, which helps to form a more comprehensive product impression. In daily life, clarify our own needs and preferences instead of being influenced by marketing or the opinions of others. Choose products that best fit personal usage habits and lifestyle. Finally, consumers can refer to evaluations and ratings from third-party organizations or those without commercial interests, which are generally more objective and reliable.

By taking these measures, consumers can more rationally evaluate and choose products, avoiding the influence of cognitive biases, thus making purchases that better align with their own interests.

Although we have successfully conducted the experiment and drawn conclusions, the study still has some limitations. The sample size, while sufficient for this experimental design, may not be

enough to generalize the results to a broader population. There is also the possibility of self-selection bias, meaning that participants who choose to take part in the study may have pre-existing biases that could affect the results. Furthermore, the specific context of the study (focusing on Apple purchases) may lead to external validity issues and may not be applicable to other product categories or markets. Lastly, the accuracy of variable measurement may also affect the conclusions of the study.

Our research provides an actionable path for future studies to explore the complex interplay between cognitive biases, availability heuristics, and digital marketing strategies. Future research can delve into how these biases affect consumers from different cultural backgrounds, such as how patriotic sentiments may influence Chinese consumers' preferences for Huawei smartphones and how other cultural factors affect global consumers' brand choices.

There is also potential to further explore how behavioral economic theories interact with digital marketing strategies, especially in the context of the increasing prevalence of social media and mobile device usage. Research could focus on how to design online content, such as advertisements, reviews, social media posts, etc., to leverage or mitigate these biases. Additionally, research could examine how companies can use cognitive biases to enhance their marketing strategies and product development. Understanding these dynamics can provide actionable strategies for companies to better target consumers and foster brand loyalty.

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