Analysis of Consumer Behavior in Bigdata Insights

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Abstract. The importance of consumer behavior research in big data analytics is becoming increasingly prominent. By analyzing big data on consumer preferences, changing demands, behavioral patterns, and trends, businesses can make more accurate decisions, optimize product design and marketing strategies, and enhance their market competitiveness. Consumer behavior research aims to explore the behaviors, motivations, and decision-making processes exhibited by consumers in the process of purchasing goods or services, in order to understand and explain the underlying psychological, social, and cultural factors. This research helps uncover the factors and processes involved in consumer decision-making, including need recognition, information search, evaluation, and choice. Understanding consumer decision behavior is crucial for businesses and marketers as it guides them in formulating more effective marketing strategies. Consumer behavior research also provides guidance for marketing strategies. By gaining a deep understanding of consumer psychology and behavior, businesses can better target markets, optimize product design, develop differentiated marketing strategies, establish brand awareness, and provide personalized products and services. Additionally, consumer behavior research helps uncover consumer needs and preferences, providing guidance for product innovation. Consumer behavior research examines the effects of social and cultural factors on consumer behavior, to gain a deeper understanding of the reasons behind consumer behavior and how marketing efforts shape and influence consumer behavior.

Keywords: Consumer Behavior, Consumer Preference, Big Data analysis.

1 Introduction

Research on consumer behavior holds significant importance in the field of big data analysis. By analyzing consumer preferences, changes in demand, behavioral patterns, and trends through big data, businesses can make more accurate decisions, optimize product design, marketing strategies, and enhance their market competitiveness. Consumer behavior studies the behaviors, motivations, and decision-making processes exhibited by consumers during the purchase of goods or services. It is of great research

A. Bhunia et al. (eds.), *Proceedings of the 2023 International Conference on Finance, Trade and Business Management (FTBM 2023)*, Advances in Economics, Business and Management Research 264,
https://doi.org/10.2991/978-94-6463-298-9_47

significance in understanding and explaining the psychological, social, and cultural factors behind consumer behavior [1-3].

Research in consumer behavior can uncover the factors and processes behind consumer decision-making, including consumer needs recognition, information search, evaluation, and choice [4-6]. This is crucial for businesses and marketers as they need to understand consumer decision behaviors in order to develop more effective marketing strategies. Consumer behavior research can provide guidance for the formulation of marketing strategies. By gaining deeper insights into consumer psychology and behavior, businesses can better target their markets, optimize product design, develop differentiated marketing strategies, build brand awareness, and offer personalized products and services. Consumer behavior research helps discover consumer needs and preferences, providing guidance for product innovation. By understanding consumer behaviors and changes in demand, businesses can develop innovative products that better meet market needs and provide superior user experiences. Consumer behavior research not only focuses on individual decisions but also examines the influence of social and cultural factors on consumer behavior. Consumer behavior is influenced not only by individual choices but also by factors such as family, friends, media, and cultural values. Studying these social influence factors helps gain a deeper understanding of the underlying reasons behind consumer behavior and how marketing efforts can shape and influence consumer behavior.

The study of consumer behavior can be traced back to the early 20th century. Here are some key milestones and major research directions in consumer behavior:

- Early Research (1900-1950): Early studies in consumer behavior primarily focused on purchase decisions and consumer psychology, such as Marshall Fisher's theory of buying motives and Frederick Heisenberg's two-factor theory.
- Psychological Orientation (1950-1970): During this period, researchers began applying principles of psychology to the study of consumer behavior. Abraham Maslow's hierarchy of needs theory was widely applied to explain consumer buying motivations and behaviors. Additionally, the development of cognitive psychology provided a new perspective for understanding consumer information processing and decision-making.
- Sociological Orientation (1970-1980): During this period, researchers began to examine the relationship between consumer behavior and social factors. They studied the influence of factors such as family, social class, culture, and socialization on consumer behavior. For example, Pierre Bourdieu's theory of "cultural capital" explored the impact of social backgrounds on consumer choices.
- Marketing Orientation (1980-1990): During this period, researchers began closely linking consumer behavior with marketing. They focused on consumer responses to advertising, promotions, and product features. Additionally, concepts such as market segmentation, target markets, and brand management started to be applied in consumer behavior research.
- Culture and Consumer Sociology (1990-Present): In recent years, consumer behavior research has increasingly focused on the meaning and role of consumption within

social and cultural contexts. Researchers have explored topics such as consumer identity, brand culture, consumer subjectivity, and sustainable consumption.

Furthermore, with the rise of the internet and big data analytics, researchers have started studying the impact of online consumer behavior and e-commerce on consumer behavior. They utilize methods such as big data analysis to achieve more accurate market predictions and analysis of supply and demand relationships. The development of these research directions has propelled advancements in the field of consumer behavior. By conducting in-depth research on consumer behavior, we can better understand consumer needs, decision-making processes, and behaviors, thereby providing more accurate guidance and decision-making basis for businesses and markets. Additionally, the evolution of consumer behavior research has also provided consumers with more choices and personalized purchasing experiences. By integrating and analyzing large amounts of consumer data, we can establish mathematical models of consumers to understand their basic information, interests, hobbies, purchasing habits, and more. This can help businesses better understand their target audience, precisely position the market, and provide personalized products and services to different consumers. Big data analysis can track and analyze the purchase decision paths of consumers, understanding their behaviors and touchpoints during the purchase process. For example, analyzing behavioral data such as website browsing, social media interactions, search engine queries, as well as conversion rates across different channels. This can help businesses optimize the purchase path, enhance user experience, and increase sales conversion rates. Through big data analysis, we can uncover potential trends and patterns in consumer demand. By analyzing historical sales data, market trends, social media data, etc., we can predict future demand changes and adjust product strategies and supply chain management accordingly to meet market demands. Big data analysis enables personalized marketing and recommendations based on consumers' past behaviors and preferences. By analyzing consumer purchase history, click behaviors, social network relationships, etc., businesses can provide personalized product recommendations, coupons, and customized marketing activities to enhance user engagement and loyalty. In conclusion, the application of big data analysis in consumer behavior can help businesses better understand consumers, forecast demand, and optimize marketing strategies.

The application and promotion of big data can change marketing behavior and consumer consumption behavior. Therefore, precise analysis of consumption behavior using big data can help improve the inevitable development trend of the industry. The analysis of tourism consumption behavior using big data technology includes data mining, data quality management, and data analysis and utilization [7, 8]. The AISAS model was first proposed by Japan Telecom Group based on the changes in consumer lifestyle in the internet era, Divide online consumer behavior into five stages: attention, interest, active search, action, and share.

Huang et al. found through EEG experiments that information emotions play a crucial role in the popularity of information, and unpopular information attracts people's attention more than popular information and is easier to retain [9]. This study used a scale to report the popularity of information among participants, while in reality, the popularity of information can be reflected through various interactive functions such as likes, reposts, and shares. Sherman et al. In addition, there is little research on the neural mechanisms behind consumer interaction behaviors such as sharing and forwarding. In fact, the choice of likes and other different interactive functions reflects the subtle psychological differences of consumers. Future research can use tools such as ERPs and fMRI to identify the psychological differences behind each interactive function, which can help marketers and content creators develop corresponding content promotion strategies based on the different psychology of consumers.

In order to better understand consumer trends so that sellers can better sell their products and make more profit, we use knowledge and models from big data analytics and consumer behavior to analyses and interpret consumer behavior. This is the age of big data, and when analyzing consumer behavior, it is possible to use big data analysis to get a clearer, more accurate and quicker picture of consumer trends and to change the product range or sales strategy to meet consumer needs. Currently, everyone's standard of living is relatively high and the demand for goods changes as people's standard of living and consumption levels change, so it is essential to use consumer behavior analysis based on big data analytics. This will enable businesses to understand consumer preferences more accurately and can provide better and more accurate services to consumers. Our main objective in creating this article is to better understand the needs of consumers, so that one can adjust our product range and sales methods to meet their increasing needs, and to facilitate others who share our vision to have a more comprehensive understanding of consumer preferences, and ultimately to achieve the goal of satisfying consumers and maximizing our own profits.

2 Analysis of Consumer Satisfaction

After making a purchase decision, consumers can evaluate their decision based on the "Buyer's Obtained Value" (BOV), which represents the actual value derived from the consumption process. If the actual experiential value is not lower than the value claimed by the seller and the expected value, then the decision is considered a successful consumption decision. Otherwise, it is deemed a failed consumption decision. The calculation formula for BOV is BOV = (PER - EXP) / EXP * 100. PER represents the Perceived Value, which is the actual value perceived by consumers after purchasing and using a product or service. EXP represents the Expected Value, which is the value consumers expect to obtain before making a purchase. A sketch of the value analysis is shown in Fig. 1. By comparing the actual experience value with the expected value, the BOV formula yields a percentage value that represents the proportion of value obtained by consumers relative to their expected value. If the BOV value is positive, it indicates that the actual experience value exceeds the expectations, meaning consumers have obtained more value than they anticipated. If the BOV value is negative, it suggests that the actual experience value falls short of expectations, indicating that consumers did not obtain the value they anticipated.

Analyzing the BOV in the context of Tesla's price reduction event allows us to assess the impact of the price reduction on the value consumers obtain from their perspective.

Firstly, we need to determine the expected value (EXP) and the perceived value (PER). The expected value represents consumers' anticipated value of owning a Tesla car, which can include factors such as vehicle performance, quality, driving experience, and environmental friendliness. The perceived value, on the other hand, reflects the actual experience and value consumers perceive after purchasing and using a Tesla car. Taking the Tesla Model 3 as an example, based on incomplete statistics, the global price reduction for Tesla cars in the first half of 2023 ranged from 15% to 20%. Let's assume a consumer expected a value of $60,000 before purchasing a Tesla and ultimately bought a Tesla model with an actual experience value of $55,000. Applying the BOV formula, we can calculate BOV = -8.33%. This indicates that the actual experience value is lower than their expected value, and the consumer's actual experience after purchasing a Tesla did not meet their expectations. Consumers may feel disappointed or dissatisfied because the value they anticipated was higher than what they actually received.

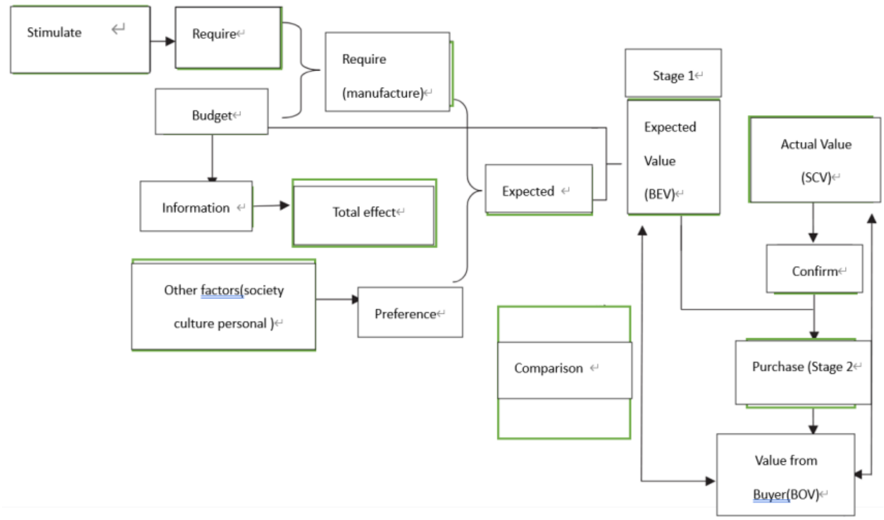

Fig. 1. A sketch of the value analysis.

The Tesla price reduction event has had a negative impact on consumers' BOV. The value consumers expected to receive when purchasing a Tesla was not fully realized, which could lead to some consumers questioning the brand and product, weakening their loyalty and willingness to repurchase from Tesla. This can also explain why, after the price reduction, Tesla owners in various regions in China expressed a decrease in trust and favorability towards the brand, and potential buyers who had not yet purchased a Tesla expressed reservations.

The consumer demand curve refers to the relationship between the quantity of a particular good or service that consumers are willing to purchase and the price of the good or service, assuming other conditions remain constant. The demand curve typically exhibits a negative slope, indicating that as the price increases, the quantity demanded decreases. The concept of the demand curve and its formula is derived from the marginal utility theory and demand theory in economics. Marginal utility refers to the additional satisfaction consumers derive from purchasing an additional unit of a good or service. Demand theory suggests that consumers tend to purchase more goods or services when prices are lower because marginal utility decreases as consumption increases. The general form of the demand curve can be represented by the following linear function Qd = a – bP. Qd is the quantity demanded, representing the quantity of goods or services that consumers are willing to purchase. P is the price of the good or service. a is the intercept of the demand curve when the price is zero, representing the maximum quantity consumers are willing to purchase (demand at a price of zero). b is the slope of the demand curve, indicating the degree to which changes in price affect the quantity demanded. The slope (b) of the demand curve is negative, indicating that the quantity demanded decreases as the price increases. The magnitude of the slope depends on the price sensitivity of consumers towards the good or service. A larger slope indicates higher price sensitivity and a greater response of quantity demanded to price changes. The derivation of the demand curve is based on consumer preferences, income levels, availability of substitutes, and other factors. When these factors change, the demand curve also shifts accordingly. Therefore, the specific form and parameters of the demand curve depend on the characteristics of the specific good or service and the relevant market.

Using the example of the Tesla Model 3, let's consider a consumer who is contemplating charging their Tesla electric car using a charging station. Initially, the consumer sets the charging time for the electric car to 2 hours per day to ensure sufficient charge for the next day's usage. In this scenario, the consumer obtains a high marginal utility because they can ensure an adequate charge and avoid the risk of the electric car running out of power. However, if the consumer decides to extend the charging time to 3 hours to further increase the reserve capacity of the electric car, the marginal utility of charging an additional hour may be relatively lower. This is because after charging for 3 hours, the additional hour of charging does not provide significant additional benefits. As the charging time continues to increase, the consumer may encounter diminishing marginal utility. For example, if the consumer decides to extend the charging time to 6 hours, surpassing the charging time required by the vehicle, the marginal utility of charging an additional hour becomes even more limited because the vehicle has already obtained sufficient charge in earlier stages.

This example illustrates the concept of diminishing marginal utility, whereby the additional benefits derived from pursuing more of a specific product or service gradually decrease. In the case of Tesla electric cars, increasing the charging time initially provides higher marginal utility, but as the charging time extends, the marginal utility of each additional hour decreases. This phenomenon occurs in many consumer decisions, where consumers need to weigh the marginal benefits and costs of pursuing more goods or services.

When it comes to Tesla and the diminishing marginal utility, one can use mathematical formulas to analyze the marginal utility of charging time in the given example. Let's assume that the consumer measures charging time (T) in hours and defines marginal utility (MU) as the additional benefit obtained from an extra hour of charging. In the initial scenario, the consumer has a marginal utility of MU1 and a charging time of

T1, which they believe ensures sufficient battery capacity. When the consumer decides to extend the charging time to T2 hours, they expect a relatively lower marginal utility (MU2) because the extra charging time provides more capacity than they need. The marginal utility can be represented as follows MU1 = f(T1) MU2 = f(T2). Assuming that the marginal utility function f is diminishing, meaning that marginal utility decreases as charging time increases, it aligns with the concept of diminishing marginal utility. One can then compare the two marginal utility values, MU1 and MU2, to assess the change in marginal utility.

If MU2 < MU1, indicating that the increase in marginal utility is smaller compared to the previous stage, we can conclude that there is a diminishing marginal utility as the consumer increases the charging time from T1 to T2. It's important to note that the specific marginal utility function f and the unit of charging time may vary depending on the actual circumstances. The provided mathematical formulas and analysis serve as an example to illustrate the relationship between Tesla and diminishing marginal utility. In practical applications, more accurate models and functions can be established based on specific situations and data to better analyze consumer behavior.

3 Hunan Provincial Museum

Previous study used the Hunan Provincial Museum as an example [10], referencing the research framework proposed by Li [11], and analyzed the application of tourism scene technology in Hunan Provincial Museums based on tourist perception. This study adopts both AHP and IPA analysis methods. AHP (Analytic Hierarchy Process) is a systematic analysis method that solves resource allocation. By establishing a hierarchical structure, qualitative judgments that are difficult to quantify are transformed into comparing the importance of several elements between pairs. The key step of AHP is the calculation of weight. Generally, the Delphi method is used to calculate the weight, but the process is cumbersome and the workload is heavy. Therefore, the paper uses the principal component weight to calculate the weight, and calculates the "tourism science and technology application index" based on the tourists' evaluation, so as to evaluate the application effect of science and technology in Xiangbo tourism scene. The IPA (Import Performance Analysis) model takes performance (measured by satisfaction) as the Y-axis and importance as the X-axis to construct a planar coordinate system. The coordinates are divided into four quadrants, namely, I, II, III, and IV, using the overall average of X and Y as the dividing line, representing "good performance", "additional benefits", "slow improvement", and "key improvement", To judge and evaluate the gap between the actual situation of each indicator and the ideal goal. The traditional IPA model has its drawbacks, as tourists' self-reported importance is influenced by satisfaction. Therefore, scholars have corrected the traditional IPA model by using partial correlation coefficients as extended importance, eliminating the influence of satisfaction, making the analysis results of the IPA model more instructive. This study used the IPA model modified by scholar Deng Weizhao for data analysis. To weaken the impact of tourist satisfaction on importance, the article measures the importance of applying technology in tourism scenarios using extended importance, which is calculated from satisfaction. For the satisfaction evaluation of each element, Si is taken as the natural logarithm and recorded as ln (Si). With ln (Si) as the independent variable and the overall satisfaction evaluation as the dependent variable, the SPSS software is used for multiple regression analysis. The partial correlation coefficient between the two is the extended importance. As shown in Fig. 2, 18 indicators are distributed within 4 quadrants based on satisfaction and extended importance

The research has drawn the following conclusions: (1) The level of technology application in Xiangbo tourism scenes is not high, and the tourism technology application index is low. (2) The technology application in tourism service scenarios is relatively rich and mature, with a high technology application index and good performance. The technology application index of public services and exhibition technology is relatively high, while the technology application index of explanation technology is slightly low. (3) There are few technology applications in tourism management scenarios, and the technology application index is low, but tourist satisfaction is high, saving resources. The passenger flow management system and intelligent parking system are both located in the well performing area. (4) There is a slight lack of technology application in tourism consumption scenarios, and the technology application index is low, which needs to be strengthened. The importance and satisfaction of ticket booking and payment are both high, and the performance is good. (5) The technology application index in tourism marketing scenarios is high, with high investment but low returns. Among them, the interactive magic wall and multimedia demonstration of ethnic dialects are located in an additional resource area, without excessive investment.

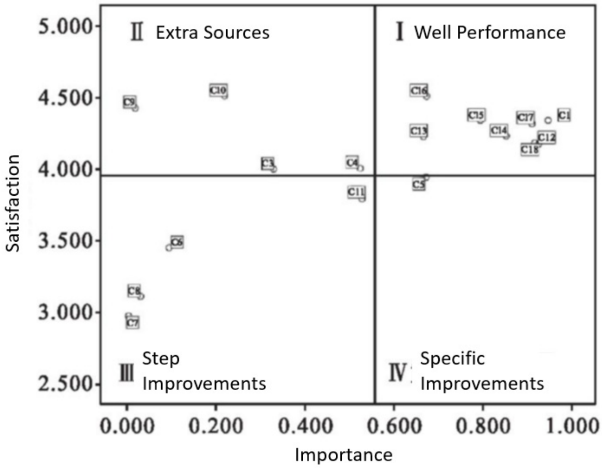

Fig. 2. The scatter of importance and satisfaction.

4 Conclusion

In summary, with the progress of network technology, it has become a very common phenomenon to apply big data to the study of Consumer behavior. Studying Consumer behavior from the perspective of big data allows us to conduct accurate analysis of consumer needs and better conduct business activities. This paper mainly introduces the research history and significance of consumer behavior, introduces the role of Big data analysis in Consumer behavior research, points out the dependent and independent variables in consumer behavior research, understands Big data analysis and its corresponding characteristics, and then focuses on the application of consumer behavior in reality with two examples of Tesla Motors and Hunan Provincial Museum. At present, big data is mainly concentrated in three ways: the Internet, the Internet of Things and traditional information systems. This article mainly conducts research on the Internet, whereas there is relatively little research on the Internet of Things. With the development of 5G, the Internet of Things has become a future trend, and consumer behavior should keep up with the times and firmly grasp the key point of the Internet of Things. These results shed light on guiding further exploration of big data implementation in consumer behavior.

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