Implementing Big Data to Understand Consumer Behaviour

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Abstract

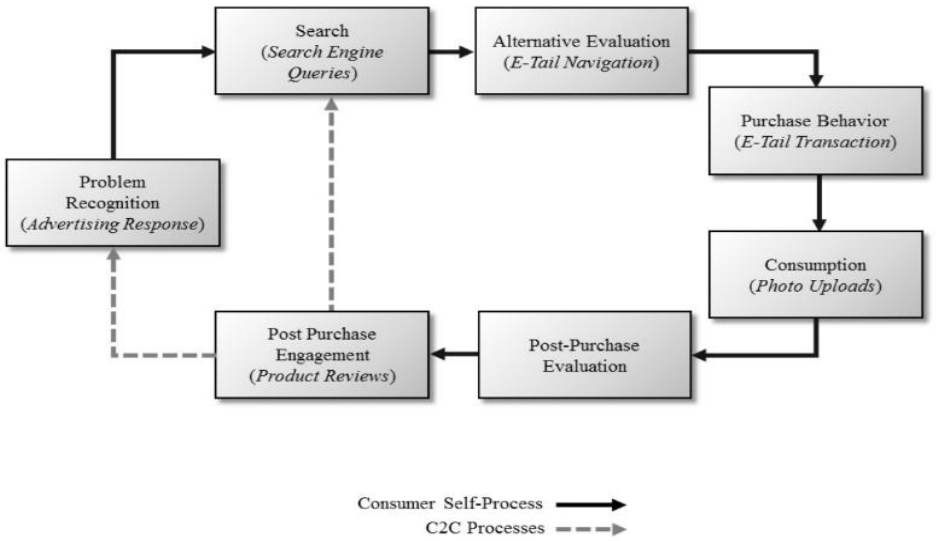
This paper aims to evaluate the potential benefits of incorporating big data in the study of consumer behaviour. The methodology involves summarizing the opportunities and changes that big data can introduce to consumer behavior research. The findings suggest that big data can enhance our understanding of the consumer decision-making process at every stage. Traditionally, consumer behaviour research relied on a priori theory followed by experimentation, but the advent of big data may alter the feedback loop between theory and results. One of the limitations of this research lies in the emergence of a new data culture in marketing practice, advocating for inductive data processing and A/B testing over human intuition-based deduction. This approach opens up possibilities for utilizing various secondary data sources. However, the use of big data may also be constrained by issues such as poor data quality, unrepresentativeness, and volatility. From a practical standpoint, managers seeking insights into consumer behaviour will require new skill sets, including proficiency in Big Data consumer analytics. Nonetheless, embracing big data in the study of consumer behaviour offers the potential for evolution and progress amid the big data revolution.

Keywords - Consumer behaviour, Big Data, Business, Technology

Introduction

Data is generated every fraction of a second in the modern digital age. Every individual contributes in some way to this data pile, whether they are browsing e-commerce websites or using social media. Consumers play a pivotal role in a market-based economy. Modern market economies have made it a priority to put consumer demand at the centre. As a result, it is vital to discuss consumer behaviour in light of big data. In the past, if someone wanted to buy a book that they had probably heard about from friends or family, they first had to visit several book stores to see if the book was actually available, and then they had to compare prices in order to decide where to buy it. These activities required time and money. The situation has fundamentally changed. The individual can now learn how to promote a book effectively via informal networks, and by just visiting an internet retailer like Amazon.com,

they can purchase the book by pressing a button, thereby saving time and energy. Accordingly, the process of buying anything got better in terms of time and money spent, but it got harder in terms of basic leadership, which has become more difficult. This study is primarily concerned with the construction of the online consumer behaviour model and its analysis.



Literature Survey

Traditional Analytical Systems for Customer Behaviour:

In the late 1970s, two primary approaches for constructing Database Management Systems (DBMS) existed. The first approach employed the hierarchical data model, exemplified by IBM's Information Management Systems, designed to accommodate the vast information storage demands of the Apollo space program. The second approach utilized the network data model, aiming to create a standardized database and address limitations of the hierarchical model, such as its inability to represent complex relationships in DBMSs. However, these models had significant drawbacks, such as the need for complex programs to handle even simple queries and limited data independence.

Following this, experimental relational DBMSs were developed, with the first commercial products appearing in the 1970s and early 1980s. Although widely used during the 80s and 90s, relational DBMSs struggled to meet the increasingly complex entity and data requirements of companies due to the expansion of their operations and applications. As a response to this complexity, two new data models emerged: Object-Relational Database Management Systems (ORDBMS) and Object-Oriented Database Management Systems (OODBMS), which adhere to the relational and object data models, respectively. The combination of OODBMS and ORDBMS represents the third generation of Database Management Systems. The advent of Big Data Analytics is triggered when data volume, velocity, or variety surpass the capabilities of IT operational systems to gather, store, analyze, and process it. While organizations can handle substantial amounts of unstructured data using

various tools, the exponential growth of data poses challenges in mining and deriving timely insights. Big Data has transitioned from experimental science projects to a crucial tool for companies, enabling telecommunication giants to understand customer satisfaction, identify causes of dissatisfaction, and predict potential customer churn. This requires processing vast amounts of loosely-structured data from diverse locations to extract the necessary information. Such analysis empowers executive management to address faulty processes or personnel and possibly retain at-risk customers.

As Big Data gains prominence, it emerges as a significant technology trend with the potential to transform the way organizations analyse and derive valuable insights from customer behavior.

CONSUMER BEHAVIOUR AND THE NEED FOR BIG DATA

Consumer behavior pertains to the actions individuals take when purchasing specific products. Analyzing such behavior offers valuable insights to marketing analysts about consumers' buying patterns. With the rise of digitalization, an enormous amount of data related to consumer buying behavior is generated every second, amounting to trillions of data pieces. Moreover, consumers exhibit diverse natures, leading to significant variations in their buying behavior. As a result, the data becomes highly diversified and increasingly complex, making conventional data analysis methods challenging to implement. At this juncture, Big Data technology plays a crucial role, as it can efficiently extract, process, and analyze vast and intricate datasets.

TYPES OF ANALYTICS FOR ANALYZING CONSUMER BEHAVIOR IN BIG DATA

There are three general subcategories of Big Data Analytics in big data technology:

Descriptive

By analysing data in this way, we can get a much clearer picture of what has already taken place. The descriptive data analytics process uses historical data, i.e. data from the past. In addition to providing a better understanding of the past events, effective analysis and interpretation of past data can prove to be a valuable tool for identifying and preventing future mistakes. An analysis of what products consumers purchased from a business in the past two months falls under this category of data analytics.

Predictive

Predictive analytics is generally used to predict the future events. Statistics and mathematics are extensively used with information technology in Predictive Analytics. Businesses could benefit from predictive analysis by being able to anticipate future situations and avoid them. If a retail outlet wants to know what products consumers are likely to buy the next month based on the past six months of buyer behavior, then Predictive Data Analytics might be used.

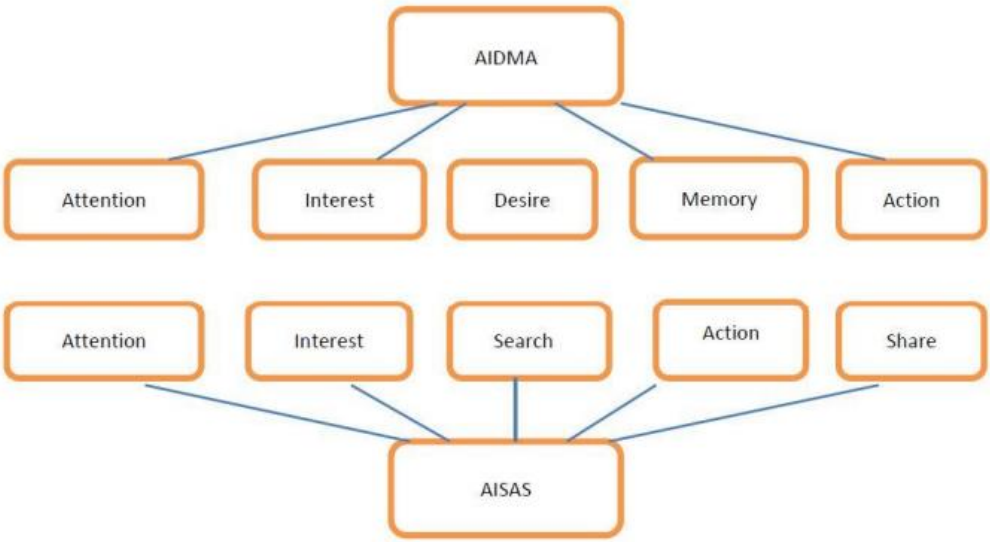
Prescriptive

Based on the information collected about the consumers' buying behavior, prescriptive data analytics can provide personalized suggestions for buying. Consumer preferences and ultimately consumer demand can be stimulated significantly by the suggestions thus provided. As an example, today it is quite normal for customers to receive advertisements from different four-wheeler brands on e-commerce websites after entering a four-wheeler showroom. A reason for this is that the Global Positioning System (GPS) collected the data of the customer.

AISAS MODEL FRAMEWORK BASED ON BIG DATA ANALYSIS

The AISAS model, proposed by Dentsu Company, offers a more suitable framework for analysing consumer behavior choices in the network economy era. According to this theory, consumers progress through five distinct stages from initial awareness of a product or service to completing the purchase process. These stages are Attention, Interest, Search, Action, and Share. This model is an evolution of the traditional AIDMA model, both of which outline the behavioural changes consumers undergo while selecting a product or service.

The key difference lies in the AISAS model's addition of two's' stages - search and share - which emphasize the network characteristic of the Internet era. These stages highlight the significance of search and sharing behaviour's in influencing consumer decisions, rather than solely transmitting information and ideas to consumers. This underscores the substantial impact of the Internet on people's lifestyles and consumer habits.



MAJOR TYPES OF CONSUMER BEHAVIOUR MODELS

1. **RFM Model**

RFM analysis is a strategy for consumer behaviour segmentation that examines customer value. RFM is an acronym for Recency, Frequency, and Monetary. Customer behavior

can be predicted by these RFM metrics because frequency and monetary value affect customer lifetime value, and recency impacts retention. By applying RFM Analysis, businesses will be able to segment their customers into homogenous groups and target marketing strategies differently to each group. These facts are shown by RFM factors:

- A recent purchase increases a customer's likelihood of responding to promotions
- The more often a customer purchases, the more satisfied and engaged they are
- Heavy spenders and low-value buyers differ based on their monetary value

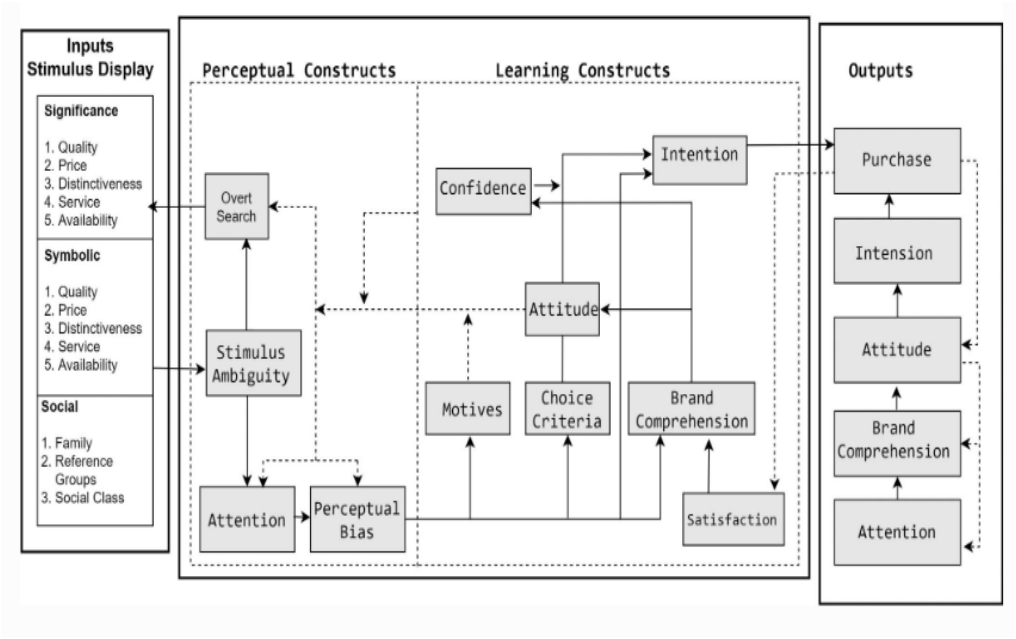
2. Black-Box Model

Black box theory explains consumer behavior by identifying the stimuli that motivate purchasers. Black box handles the stimuli (advertisements and other forms of promotion about the product) that are presented to a buyer by the marketer and the environment. A model consists of three major components: the environment, the buyers' black box, and the buyers' responses.

3. Howard–Sheth Model

The buyer model, introduced in 1969 by John Howard and Jagdish Sheth, adopts an input/output or system-based approach to purchasing and employs a problem-solving perspective. Howard introduced the concept of the learning process in buying. Brand loyalty is established through customer satisfaction, and buyers switch brands when they experience dissatisfaction. In other words, this paradigm operates on the premise that stimuli act as inputs, leading to various outputs such as attention to specific stimuli and eventual purchases. Between these inputs and outputs, there are variables that impact perception and learning.

These variables are "hypothetical" as they cannot be immediately quantified when they occur, shedding light on the complex decision-making process of consumers.



a) Inputs Stimulus Display

The input variables in the consumer's environment consist of information from three distinct types of sources. First, significant information includes physical brand attributes such as quality, pricing, uniqueness, service, and availability. Second, symbolic information encompasses verbal or visual product attributes, including quality, price, distinctiveness, service, and availability. Lastly, the consumer's social environment serves as a source of information, encompassing details about a product or service originating from family, groups, society, and culture in general.

b) Perceptual Constructs

The perceptual constructs are focused on how consumers acquire and process data from input variables. When exposed to information, a buyer pays attention to it, influenced by their sensitivity, desire, and receptivity to the information. However, not all information is effectively absorbed, and the intake can be hindered by perceived ambiguity and irrelevance, known as stimulus ambiguity.

On the other hand, the learning constructs are concerned with buyer knowledge, the formation of attitudes and beliefs, and the ultimate decision-making process. These seven learning constructs encompass various aspects, ranging from a buyer's motivation for a purchase to their satisfaction with the purchase. The combination of these constructs ultimately leads to a response output or a purchase. Motives, in this context, represent the underlying reasons that drive individuals to take action or make purchases.

c) Response Outputs (Output Variables)

The buyer's response to stimulus inputs is referred to as the buyer's action or output variables. The five components of the response outputs, according to Howard and Sheth, are attention, comprehension, attitude, intention, and purchase. These might be organised in a hierarchy, with purchase at the top and attention at the bottom.

- The amount of information a person really absorbs and stores is known as comprehension; in this context, it relates to brand understanding, or a customer's familiarity with a brand's product or service category.

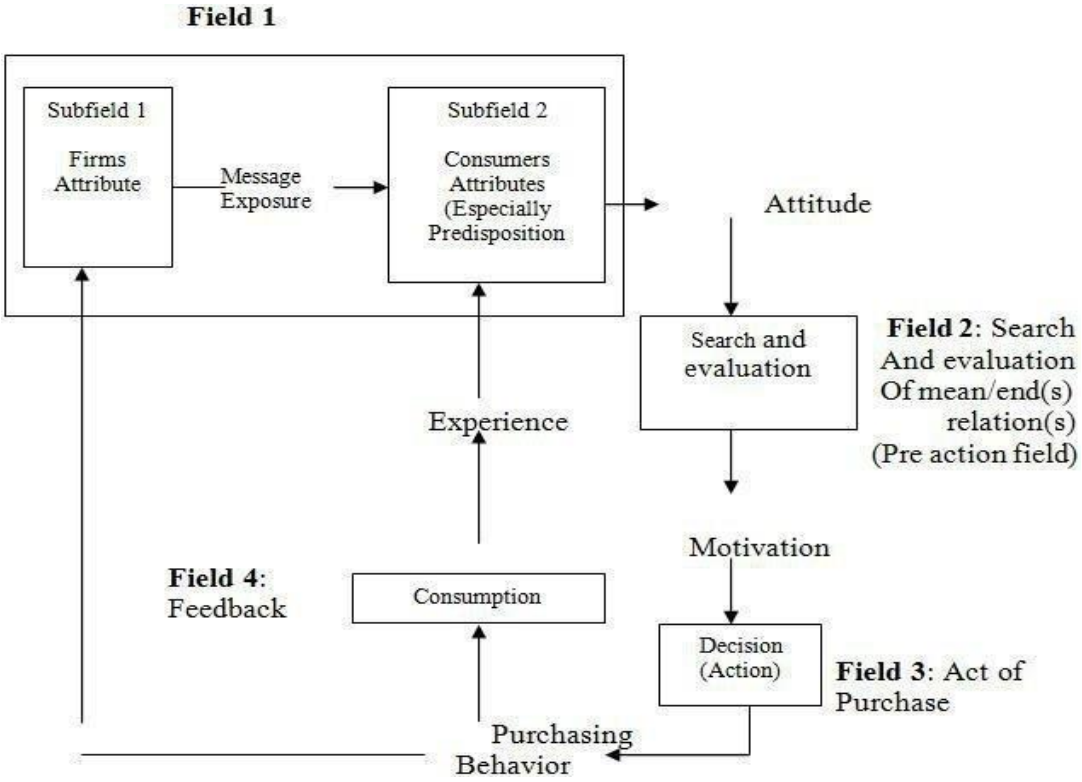
- His judgement of the brand and his likes and dislikes based on the brand's potential are reflected in his attitude, which is a composite of cognition, affect, and behaviour toward the offering.

- The buyer's intention to purchase or decline to purchase a specific item is referred to as intention.

- The act of purchasing itself is referred to as purchase behaviour. The other four components work together to produce the buying behaviour.

4. Nicosia Model

Nicosia (1976) proposed the Nicosia model of customer behavior, which centre’s on the decision-making process of purchasing a new product. This model views human behavior as the output of a system where stimuli act as inputs. From a marketer's perspective, the Nicosia model elucidates the consumer's purchasing behavior during the decision-making process.



Stage I

Firm’s Attributes and Consumer’s Attributes: The firm's attributes and the consumer's attributes are the two sub-stages that make up the first stage. A company's advertisement reaches the consumer's preferences. A specific attribute may emerge depending on how the consumer interprets the message, and this becomes the input for stage two.

Stage II

Search and Evaluation: Stage II entails looking for and assessing the advertised goods and other options. If the outcome of this process is a desire to purchase something, that desire becomes the third input.

Stage III

Decision: Motivation will lead to a decision through persuading the consumer to buy the firm's items from a particular retailer. The act of purchasing is the third field.

Stage IV

Feedback: Use of the purchased item is the fourth field. Following the purchase of the goods, both the company and the consumer may provide feedback.

- Firm’s feedback - Sales report from the company

- Consumer’s feedback - consumers' attitudes about future messages from a company depending on their experiences and predispositions.

CONCLUSION

Implementing big data to understand consumer behavior has emerged as a transformative approach in the modern business landscape. By harnessing the power of massive and diverse datasets, businesses can gain valuable insights into consumers' preferences, needs, and purchase patterns. The comprehensive analysis of consumer behavior at various stages of the decision-making process allows companies to tailor their marketing strategies, product offerings, and customer experiences to meet individualized demands. It is important to acknowledge the ethical considerations surrounding consumer data privacy and security. Responsible data management practices and compliance with regulatory requirements are essential to maintain consumer trust and confidence in utilizing big data for understanding consumer behavior.

As technology continues to evolve, the potential for big data in understanding consumer behavior will only expand. Businesses that embrace this transformative approach stand to gain a competitive edge in today's data-driven world, fostering enduring relationships with their customers and driving sustainable growth in the ever-evolving marketplace.

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