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Understanding Consumer Behavior Through Big Data Analytics: Evidence from the Smartphone Industry

Bouaddi Mohamed[1*], Beddaa Mohammed[2], Khaldi Siham[3]

[1*,3]*Faculty of Legal, Economic and Social Sciences, University Moulay Ismail, Meknes, Morocco*
[2]*Higher School of Technology, Mohammed First University, Oujda, Morocco*
[1*]m.bouaddi@edu.umi.ac.ma ; [2]mohammed.beddaa@ump.ac.ma; [3]s.khaldi@umi.ac.ma

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ABSTRACT

In an era dominated by digital interactions, the utilization of Big Data has become essential for businesses striving to comprehend and anticipate consumer behavior. This study investigates the impact of Big Data on understanding consumer behavior and enhancing customer satisfaction within the smartphone market. A quantitative research design was employed, involving a sample of 300 smartphone users surveyed through a structured questionnaire. Utilizing Structural Equation Modeling (SEM), the analysis revealed significant positive relationships: Big Data positively influences the understanding of consumer behavior and consumer satisfaction, while a deeper understanding of consumer behavior also enhances satisfaction. The strong statistical significance of these findings underscores the strategic value of Big Data for businesses aiming to optimize customer experiences and maintain competitive advantage. Furthermore, the study highlights key recommendations for organizations looking to leverage Big Data effectively. Companies should invest in robust data analytics platforms, implement advanced analytics tools for effective customer segmentation, and utilize machine learning algorithms to anticipate consumer trends. Ethical considerations are paramount; organizations must ensure transparency in data collection and comply with privacy regulations to foster consumer trust. Future research should explore the long-term effects of Big Data utilization on consumer satisfaction and examine its applications across different industries. Overall, this study affirms that effective data analytics not only enhances consumer insights and satisfaction but also strengthens relationships between businesses and their customers in an increasingly competitive market landscape.

1. Introduction

In a world awash with data, Big Data emerges as a powerful lever for businesses seeking to understand and anticipate consumer behavior. (Mayer-Schönberger & Cukier, 2013). The rapid expansion of digital interactions, through social media, e-commerce, and mobile applications, has resulted in an exponential increase in the amount of data generated by users. (Zikopoulos el al., 2012) This influx of information provides companies with unprecedented opportunities to gain insights into consumer preferences, habits, and motivations. (Rosário & Dias, 2023) However, harnessing this data effectively requires sophisticated analytical tools and strategies, making it essential for companies to analyze this information to enhance their marketing strategies and optimize customer satisfaction. (Ali, 2023)

This dynamic raises a central question: What is the impact of Big Data on the understanding of consumer behavior and their satisfaction? Understanding this relationship is vital for businesses that aim to create more personalized and effective marketing strategies. By effectively utilizing Big Data, organizations can not only respond to existing consumer needs but also anticipate future trends, thus staying ahead in a competitive marketplace.

The context of this study lies at the intersection of digital transformation and evolving consumer expectations. As technology continues to advance, consumers are becoming increasingly savvy and demanding. (Kotler & Keller, 2016) They expect tailored experiences and immediate responses from brands, which adds pressure on companies to leverage data effectively. (Amoo el al, 2024) In this increasingly complex business environment, the ability to analyze large volumes of data can make the difference between success and failure. (Mikalef el al, 2019) Understanding how Big Data influences purchasing decisions and consumer satisfaction levels is crucial for any modern business strategy. (Adaga el al, 2023)

To address this question, we will start firstly by establishing a conceptual framework that outlines the various concepts related to Big Data, consumer behavior, and customer satisfaction. This section will be followed by a comprehensive review of relevant literature that examines the impact of Big Data on these dimensions, drawing on existing theories and last researches to frame our analysis. After, we will focus on an empirical framework, presenting a study aimed at analyzing the impact of Big Data on the understanding of smartphone consumer behavior and their satisfaction. This empirical investigation will involve collecting and analyzing data from smartphone users to assess how effectively Big Data analytics can inform business strategies and improve customer satisfaction.

This approach will not only illuminate the relationships between these concepts but also provide practical insights for businesses looking to leverage massive data to improve their understanding of consumers and enhance their satisfaction. By demonstrating the tangible benefits of utilizing Big Data, our study aims to offer actionable recommendations for companies seeking to adapt to the rapidly changing digital landscape.

2. Literature Review

2.1. Big Data

2.1.1. Definition and Tools

Big Data refers to the phenomenon of handling vast datasets that are defined by five key dimensions: volume, velocity, variety, veracity, and value (Laney, 2001). Volume relates to the sheer amount of data generated every second, necessitating robust storage solutions. Velocity indicates the speed at which data is produced and processed, which is essential for real-time decision-making. Variety encompasses the different types of data, structured, semi-structured, and unstructured, that organizations must manage. Veracity pertains to the accuracy and trustworthiness of the data, which is crucial for reliable analyses. Lastly, value represents the potential insights that can be derived from analyzing this data. (Gandomi, 2015)

In today's digital landscape, these dimensions are vital for how businesses collect, store, and analyze information. Key tools for managing Big Data include Hadoop and Apache Spark. Hadoop is designed for distributed processing of large datasets through a clustered architecture, enabling efficient storage and analysis of diverse data types. (Sewal, 2023) It utilizes a MapReduce programming model that allows for the parallel processing of data across multiple nodes, significantly speeding up analysis. (Ma el al, 2023) Conversely, Apache Spark offers a high-performance computing environment optimized for real-time analytics. It supports in-memory processing, drastically improving the speed of data retrieval and analysis, making it particularly beneficial for businesses requiring immediate, actionable insights (Zikopoulos el al., 2012).

2.1.2. Applications of Big Data

The applications of Big Data span a wide range of sectors, each benefiting from the ability to analyze vast amounts of data to improve decision-making and operational efficiency. In healthcare, data analytics facilitates epidemic predictions and personalized treatments, enhancing patient care and resource allocation (Raghupathi & Raghupathi, 2014; Khanra el al., 2020). Predictive analytics can identify health trends, allowing for timely interventions that save lives. In the financial sector, institutions employ machine learning algorithms to detect fraud and assess credit risks. Brightwood (2024) demonstrates that predictive analytics plays a critical role in anticipating suspicious behaviors, thereby enhancing the security of financial transactions and minimizing losses. In marketing, companies leverage consumer data to develop targeted advertising campaigns. Wedel and Kannan (2016) explain that by analyzing consumer preferences and behaviors, organizations can optimize their return on investment, ensuring that marketing messages reach the most receptive audiences. Transport companies also utilize data analytics to streamline logistical operations and forecast demand trends. The application of predictive models enhances inventory management, enabling businesses to anticipate market fluctuations and improve overall operational efficiency. (Ghodake, 2024; Kark, 2024).

2.1.3. Challenges of using Big Data

Despite its numerous advantages, the utilization of Big Data presents significant challenges, particularly regarding data privacy and security. (Ngesa, 2024) The implementation of regulations such as the General Data Protection Regulation (GDPR) in Europe has heightened awareness of ethical issues surrounding the collection and use of personal data (Voigt & Von dem ; Bussche, 2017). Organizations must navigate these regulations carefully to avoid legal repercussions and maintain consumer trust. Another major challenge involves algorithmic biases, which can emerge from using non-representative data. (Akter, 2022) Such biases may lead to unfair decisions and discrimination, emphasizing the necessity for ethical and responsible data handling (O'Neil, 2016). Businesses must critically assess how their data models can influence outcomes and ensure their analyses are based on diverse and equitable datasets.

2.2. Consumer Behavior

2.2.1. Definition of consumer behavior

Consumer behavior encompasses all the actions and decisions an individual makes during the purchasing, usage, and evaluation of products and services. This concept extends beyond the mere act of buying; it integrates various attitudes, perceptions, and influences that guide these decisions. According to Schiffman and Kanuk (2010), consumer behavior manifests in diverse contexts, ranging from initial product exploration to the final decision-making process. Moreover, it is important to note that Blackwell el al. (2006) emphasize that this behavior arises from a complex interplay of individual, social, cultural, and environmental factors. For instance, individual factors include personal preferences and psychological influences, while social factors encompass family, friends, and broader societal influences that shape consumer attitudes. Additionally, cultural factors, which include values, customs, and traditions, further inform consumer choices, illustrating that behavior is often a reflection of wider societal trends and influences.

2.2.2. Models of consumer behavior study

The study of consumer behavior has evolved through several theoretical models, each attempting to explain how and why consumers make decisions. (Roy el al, 2022) Among these models, the rational decision-making model posits that consumers evaluate alternatives based on objective criteria, such as price, quality, and features (Kotler & Keller, 2016). This model assumes that consumers act logically, seeking to maximize their utility during the purchasing process. In contrast, another influential model is the AIDA model (Attention, Interest, Desire, Action), which describes the psychological stages consumers go through before making a purchase. Proposed by St. Elmo Lewis, this model begins with capturing the consumer's attention, subsequently arousing their interest, generating desire, and culminating in the purchasing action (Purbaningsih el al., 2022). This framework is particularly useful for marketers, as it highlights the importance of engaging consumers at each stage of the purchasing process. Additionally, Rogers' (1962) diffusion of innovation model explores how new ideas and technologies are adopted by consumers. This model categorizes adopters into distinct groups—innovators, early adopters, early majority, late majority, and laggards—thereby highlighting the factors that influence the adoption of new products. Understanding these dynamics can significantly aid businesses in tailoring their marketing strategies to effectively target each segment of adopters, ultimately enhancing the chances of successful product launches.

2.2.3. Factors influencing consumer behavior

Consumer behavior is influenced by a multitude of factors that can be grouped into three main categories: psychological, sociocultural, and personal factors. First, psychological factors include motivation, perception, beliefs, and attitudes. For example, Maslow's (1943) hierarchy of needs posits that individuals are motivated by a series of needs, ranging from basic physiological requirements to higher-level needs such as esteem and self-actualization. This framework suggests that consumers will seek products and services that fulfill their most pressing needs at any given time. Next, sociocultural factors play a crucial role in shaping consumer behavior. Culture, subcultures, and reference groups profoundly influence purchasing preferences and choices. Hawkins el al. (2010) note that social values and norms dictate what is considered desirable or acceptable in a given society, thereby guiding consumer behavior. For instance, a culture that prioritizes sustainability may see consumers favoring eco-friendly products over conventional alternatives. Furthermore, personal factors such as age, gender, income level, and lifestyle significantly influence purchasing behaviors. Research indicates that younger consumers are more likely to adopt digital technologies and engage with brands online than older generations (Prensky, 2001; Yao el al., 2021). The fact of understanding these personal factors allows marketers to segment their audiences more effectively and tailor their messaging accordingly.

2.2.4. Evolution of consumer behavior in the digital age

The digital age has radically transformed consumer behavior, leading to profound implications for how individuals interact with brands. With access to vast amounts of online information, consumer reviews, and the impact of social media, the way individuals research and evaluate products has significantly changed (Mangold & Faulds, 2009). Consequently, consumers are not only better informed but also more interconnected, which in turn influences their expectations and purchasing decisions. Recent studies have increasingly focused on concepts such as user experience (UX) and the customer journey (Sinha & Fukey, 2020). These approaches aim to understand how consumers interact with brands across various touchpoints, both online and offline. According to Muntaqheem (2019) and Zamfirache el al. (2024), each stage of the customer journey—awareness, consideration, purchase, and post-purchase—is crucial for shaping consumer perception and satisfaction. For instance, a seamless online shopping experience can enhance customer satisfaction and foster loyalty. Moreover, Lemon and Verhoef (2016) emphasize that businesses must adapt their strategies to meet the evolving needs and preferences of consumers in a constantly changing digital environment. This includes leveraging data analytics to gain insights into consumer behavior, personalizing marketing efforts, and ensuring a cohesive brand experience across all platforms. As consumer behavior continues to evolve with technological advancements, organizations must remain agile and responsive to stay competitive.

2.3. Consumer Satisfaction

2.3.1. Definition of Satisfaction

Consumer satisfaction is a complex and multidimensional concept that refers to the degree to which an individual evaluates a product, service, or experience positively or negatively. (Mu el al, 2021) It encompasses not only the act of purchase but also the emotional responses that follow, stemming from a comparison between the expectations an individual holds and the actual outcomes they experience. According to Oliver (1980), satisfaction can be viewed as an emotional state arising from this evaluative process. Therefore, it is crucial for businesses to understand consumer satisfaction, as it directly influences customer loyalty, brand reputation, and overall business performance. (Singh el al, 2023) Ultimately, satisfied customers are more likely to remain loyal and engage in repeat purchases, making satisfaction a key focus for organizations aiming for long-term success. (Khadka,2017)

2.3.2. Models of consumer satisfaction

To better understand and measure consumer satisfaction, several theoretical models have been developed. One of the most influential is the Disconfirmation of Expectations Model, proposed by Oliver (1980). This model asserts that satisfaction is determined by the difference between consumers' expectations and their actual experiences. Specifically, if the actual experience surpasses expectations, the consumer feels satisfied; conversely, if it falls short, dissatisfaction occurs. Thus, this model highlights the importance of managing consumer expectations and ensuring that marketing promises align with actual product performance. Another notable model is the User Satisfaction Scale Model, which emphasizes both functional and emotional dimensions of user experience. This model evaluates satisfaction across various criteria, such as service quality, product quality, and overall customer experience (Bob el al., 2016). By considering multiple facets of user interactions, this model provides a comprehensive understanding of the factors that contribute to overall satisfaction.

2.3.3. Factors influencing consumer satisfaction

Numerous factors influence consumer satisfaction, which can be categorized into several key areas. First and foremost, product and service quality is paramount. Research indicates that high perceived quality is one of the leading drivers of satisfaction (Zeithaml el al., 1996). Therefore, companies must focus on delivering quality products and services to enhance consumer satisfaction. In addition to quality, expectations and experiences significantly shape consumer satisfaction. These expectations can be influenced by advertising campaigns, word-of-mouth recommendations, or prior experiences with the brand (Patterson & Spreng, 1997). As a result, managing consumer expectations through effective communication is vital for achieving satisfaction. Another crucial factor is the price-value ratio. Consumers are constantly evaluating the relationship between cost and perceived benefits when making purchasing decisions. A favorable price-value ratio enhances consumer satisfaction, as individuals seek products or services that offer good value for their investment (Supriadi el al., 2023). Consequently, when consumers believe they are receiving quality at a fair price, their overall satisfaction tends to rise. Lastly, the interaction with staff in service contexts can profoundly affect satisfaction levels. Positive interactions characterized by effective communication and a friendly attitude from staff can significantly enhance the consumer experience (Bitner, 1990). Therefore, training employees to provide excellent customer service is essential for fostering higher satisfaction levels.

2.3.4. The importance of consumer satisfaction

The significance of consumer satisfaction extends beyond individual transactions; it plays a critical role in shaping the overall success of businesses. According to Brewis el al. (2023), high levels of consumer satisfaction contribute to a positive reputation, customer retention, and increased profitability. Satisfied customers are more likely to return for future purchases and recommend the brand to others, thereby creating a cycle of loyalty and advocacy that benefits the business. Furthermore, in an increasingly competitive market, consumer satisfaction can serve as a vital competitive advantage (Anderson & Mittal, 2000). By prioritizing consumer satisfaction, companies can build a loyal customer base that not only drives revenue but also enhances brand loyalty and market position (Rust el al., 1993). In conclusion, understanding and improving consumer satisfaction is essential for businesses aiming to thrive in a dynamic marketplace.

3. The impact of Big Data on understanding consumer behavior and satisfaction: A literature Review

Before presenting the literature review regarding the impact of Big Data on understanding consumer behavior and satisfaction, we would like to introduce the theories used to underpin the relationships between these concepts.

3.1. Mobilized theories

For our study, we have used several key theories to understand the relationship between Big Data, consumer behavior, and satisfaction. The Theory of Planned Behavior (TPB) by Ajzen (1991) consists of three main components: attitudes, which pertain to what consumers think about Big Data analytics; subjective norms, which refer to social influences on purchasing decisions; and perceived behavioral control, which denotes consumers' perceived ability to act based on data-driven recommendations. This theory helps explain how these factors influence consumers' purchase intentions.

The Expectancy Disconfirmation Theory (EDT) by Oliver (1980) is based on the gap between consumers' expectations and the actual performance of products or services. Expectations are often shaped by prior research or recommendations, while actual performance is determined by the experience encountered post-purchase. When performance exceeds expectations, it leads to increased satisfaction; conversely, underperformance may result in dissatisfaction (Oliver, 1980).

The Customer Experience Management (CEM) framework focuses on the touchpoints between the consumer and the brand, where each interaction represents an opportunity to enhance the customer experience. By leveraging data analysis, businesses can offer personalized experiences based on past behaviors and consumer preferences, thereby increasing engagement and satisfaction. Additionally, gathering feedback allows for strategy adjustments and continuous improvement of the overall experience (Lemon & Verhoef, 2016).

Data-Driven Decision Making (DDDM) relies on principles such as predictive analytics, which uses algorithms to forecast consumer behaviors, and market segmentation, which divides the market into distinct segments based on behavioral data. This enables companies to target their marketing efforts more effectively and optimize resources (Davenport & Harris, 2007).

Finally, the Technology Acceptance Model (TAM) focuses on perceived usefulness and perceived ease of use. Perceived usefulness measures consumers' belief that a technology (such as a Big Data-driven shopping application) will enhance their efficiency, while perceived ease of use relates to the simplicity of using that technology (Davis, 1989).

This theoretical framework integrates these models to deeply explore the relationship between Big Data, consumer behavior, and satisfaction.

3.1. The role of Big Data in analyzing consumer behavior

The advent of Big Data has fundamentally transformed the commercial landscape, providing businesses with powerful tools to analyze consumer behavior. (Li el al, 2022). Big Data refers to vast and complex datasets that require advanced tools for processing and analysis (Manyika el al., 2011). In the context of consumer behavior, Big Data encompasses information from various sources, including social media, online transactions, and customer journey data. (Sarprasatham, 2016). The utilization of Big Data enables companies to analyze purchasing patterns, preferences, and consumption trends. According to Qiu el al (2023) the analysis of Big Data enhances the understanding of consumers' motivations and purchasing behaviors.

Various data analysis techniques, such as machine learning, data mining, and predictive analytics, are employed to extract meaningful information from Big Data (Jamarani el al., 2024). These techniques allow for the discovery of hidden patterns and the anticipation of future behaviors (Jivrajani el al, 2023), further enriching the understanding of consumer behavior.

- H1: The analysis of Big Data has a positive impact on the understanding of consumer behavior.

3.2. The impact of Big Data on consumer satisfaction

Consumer satisfaction is a key indicator of commercial performance. (Suchánek & Králová, 2015) The analysis of Big Data can influence consumer satisfaction in several ways. (Ju, 2022). Companies that effectively harness Big Data can offer more personalized experiences to consumers. (Satish & Yusof, 2017) For instance, analyzing customer preferences enables targeted product recommendations, thereby increasing the likelihood of satisfaction (Lemon & Verhoef, 2016). Furthermore, Big Data allows companies to better anticipate the needs and expectations of consumers. (Tian, 2021) A prime example is Netflix, which uses data analysis algorithms to recommend films and shows based on users' past behaviors, thereby helping to maintain satisfaction levels (Wu, 2023). This anticipatory capability reinforces the notion that Big Data improves customer satisfaction by creating a more tailored experience. (Bathla and Ahuja, 2024)

- H2: The analysis of Big Data has a positive impact on consumer satisfaction.

3.3. The effect of understanding consumer behavior on consumer satisfaction

Studying consumer behavior has a great importance in marketing strategies (Bouaddi & Khaldi, 2023). A better understanding of consumer behavior can have a direct impact on satisfaction levels. (Rusdian el al, 2024) Businesses that thoroughly grasp their customers' behaviors can be more responsive and agile, quickly adapting to changes in preferences. This responsiveness is often correlated with increased customer satisfaction (Wang el al., 2016).

Moreover, an in-depth understanding of customer preferences through Big Data analysis can lead to greater customer loyalty. (Nurhilalia & Saleh, 2024) Satisfied consumers are more likely to return and recommend a brand, contributing to the long-term sustainability of businesses (Al-Msallam, 2015; Samsudin et al., 2022). By creating a feedback loop where understanding informs strategies, companies can continuously improve their offerings and enhance customer satisfaction.

- H3: A better understanding of consumer behavior leads to an increase in their satisfaction.

Based on the review of literature that we have just presented, in addition to the hypothesis that we have concluded, the conceptual model underlying our research is designed to illustrate the relationships between Big Data, consumer behavior understanding, and consumer satisfaction. This model in Figure 1 posits that effective Big Data analysis not only enhances the understanding of consumer behaviors and motivations but also significantly influences overall consumer satisfaction. By establishing a clear framework, the model serves as a guide for investigating these relationships and testing our hypotheses through empirical research.

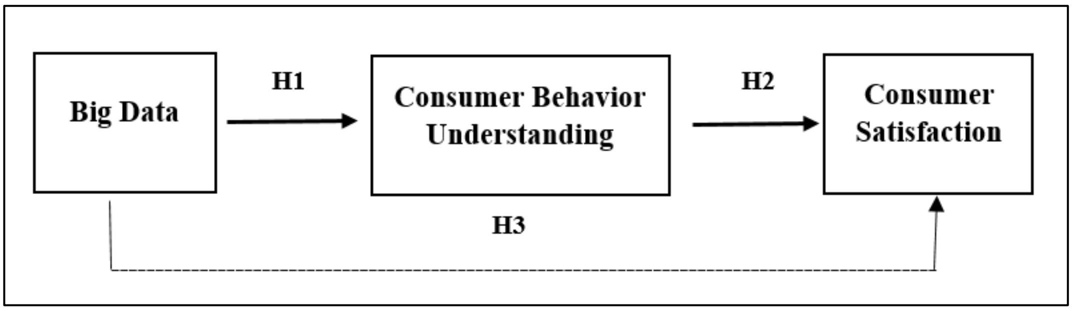

Fig.1. Conceptual framework of our research

3. Research Methods

Design

This study employed a quantitative research design rooted in a positivist epistemology. Positivism emphasizes the need for objective measurement and analysis of social phenomena, which is crucial for establishing reliable conclusions. By utilizing this approach, the study aims to systematically formulate and rigorously test hypotheses about the relationships between Big Data, consumer behavior, and consumer satisfaction. This design minimizes subjective biases, ensuring that findings are based on observable data rather than personal interpretations. This method is particularly suited for examining patterns and correlations within large datasets.

Participants and Procedure

The participants were exclusively smartphone consumers, selected from a parent population that reflects diverse demographic and behavioral traits. A convenience sampling method was employed, yielding a sample size of 300 respondents who were readily available and willing to engage in the study. This method allowed for a practical approach to participant recruitment, ensuring that the data collected could represent various consumer behaviors and preferences. Participants were chosen based on their willingness to complete a structured questionnaire, thus facilitating a broader understanding of the factors influencing smartphone usage.

Data Collection Method

Data were collected using a structured questionnaire developed from existing literature, ensuring that the measurement indicators for each latent variable were relevant and well-defined. The questionnaire included clear and concise questions designed to be easily understood by respondents. A Likert scale was utilized to quantify responses, allowing participants to express varying degrees of agreement or disagreement. To maximize response rates and enhance accessibility, the questionnaire was administered via online platforms, which also facilitated faster data collection and analysis.

Data Analysis Method

Data analysis was conducted using Structural Equation Modeling (SEM) with SmartPLS software (Hair el al., 2014). It was chosen due to its suitability for exploratory studies, small sample size compatibility, and ability to handle complex models. The analysis process began with the selection of relevant measurement indicators to ensure the validity and reliability of the constructs. The measurement model was assessed for both convergent and discriminant validity. Convergent validity was evaluated using Average Variance Extracted (AVE), while discriminant validity was assessed through the Fornell-Larcker criterion (Fornell & Larcker, 1981). Following this, the structural model was estimated to validate causal relationships, with path coefficients calculated to determine the strength of the relationships among the variables. This rigorous analysis aimed to provide insights into how Big Data influences consumer behavior and satisfaction, contributing to a deeper understanding of the underlying dynamics in the smartphone market.

4. Results and Discussions

4.2. Measurement Model

4.2.1. Selection of measurement indicators

The first step of our study involved selecting relevant measurement indicators for each latent construct (Table 1) to ensure the accuracy and reliability of our results.

First for the independent variable "Big Data," we have identified three key indicators: the volume of data collected, the variety of data sources, and the speed of data analysis. These indicators were chosen for their ability to reflect the complexity of Big Data and their relevance in the context of analysis.

Second, for the mediating latent variable «Understanding Consumer Behavior," we have selected indicators such as the identification of purchasing trends, consumer segmentation, and offer personalization.

Finally, to measure the dependent latent variable "Consumer Satisfaction," we have selected three indicators: overall satisfaction with the product, likelihood of recommendation, and brand loyalty.

Table 1. Measures of latent constructs

Latent construct	Indicator	Description
Big Data (BD)	BD1: Volume of collected data	Quantity of data analyzed
	BD2: Variety of data sources.	Diversity of sources used
	BD3: Speed of data analysis.	Speed of analysis and decision-making
Understanding Consumer Behavior (UCB)	UCB1: Identification of purchasing trends.	Ability to detect purchasing patterns
	UCB2: Consumer segmentation	Creation of segments based on behaviors
	UCB3: Personalization of offers	Use of data for personalized recommendations
Consumer Satisfaction (CS)	CS1: Overall satisfaction.	General evaluation of satisfaction
	CS2:Probability of recommending the product.	Propensity to recommend the products
	CS3: Brand loyalty.	Level of loyalty to the brand

5.2.2. Analysis of the reliability of measurement indicators

The reliability of measurement scales is crucial for ensuring that the indicators used in our study provide consistent and accurate results. (Cortina, 1993) To evaluate reliability, we have calculated Cronbach's Alpha coefficient for each latent construct. A coefficient above 0.70 is generally considered acceptable, while a coefficient above 0.80 indicates good reliability.

The results in Table 2 indicate that the indicators for "Big Data" have a Cronbach's Alpha of 0.84, demonstrating good reliability and suggesting that the measurement captures the complexity of Big Data effectively. Similarly, the construct "Understanding Consumer Behavior" has an Alpha of 0.79, which is also within the acceptable range, indicating that the indicators successfully reflect consumer behavior dynamics.

Finally, the "Consumer Satisfaction" construct achieved the highest reliability with a Cronbach's Alpha of 0.86, classified as very good reliability. This high level of reliability suggests that the indicators measuring consumer satisfaction are particularly robust and trustworthy, enhancing confidence in the conclusions drawn from this aspect of the study.

Overall, the strong reliability of these measurement scales provides a solid foundation for further analysis and interpretations in our research.

Table 2. Construct Reliability

Construct	Number of Indicators	Cronbach's Alpha (α)
Big Data	3	0.84
Understanding Consumer Behavior	3	0.79
Consumer Satisfaction	3	0.86

5.2.3. Convergent and discriminant validity

Following the assessment of reliability, we proceeded to evaluate the convergent and discriminant validity of our measurement model.

5.2.3.1. Convergent validity

Convergent validity was measured using the Average Variance Extracted (AVE). The results in table 3 indicated that all AVE values exceeded the threshold of 0.50. This threshold signifies that the indicators share a substantial proportion of variance with their respective constructs, thereby reinforcing convergent validity.

Table 3. Results of convergent validity

Indicator	Factor Loading (λ)	Convergent Validity (AVE)
BD1	0.78	0.60
BD2	0.83	0.60
BD3	0.76	0.60
CBC1	0.72	0.55
CBC2	0.75	0.55
CBC3	0.80	0.55
SC1	0.85	0.65
SC2	0.81	0.65
SC3	0.79	0.65

The factor loadings, which indicate how well each indicator represents its construct, were all above the acceptable threshold of 0.70. This further substantiates that the indicators effectively measure their intended constructs.

5.2.3.2. Discriminant validity

The analysis of discriminant validity was conducted according to the Fornell-Larcker criterion. This involves comparing the square root of the AVE for each construct with the correlations between constructs. The results in Table 4 demonstrated significant findings that strengthen the robustness of our model.

Table 4. The results of discriminant validity using Fornell-Larcker criterion

Construct	Big Data	Understanding consumer behavior	Consumer satisfaction
Big Data	0.81		
Understanding consumer behavior	0.60	0.84	
Consumer satisfaction	0.55	0.65	0.87

The “Big Data” construct has an AVE square root of 0.81, which is greater than its correlations with “Understanding consumer behavior” (0.60) and “consumer satisfaction” (0.55). Similarly, the “understanding consumer behavior” construct exhibits an AVE square root of 0.84, surpassing its correlation with “consumer satisfaction” (0.65). Finally, the “consumer satisfaction” construct shows an AVE square root of 0.87, which is also higher than its correlations with the other constructs.

These findings clearly indicate that each construct measures a distinct concept, thus validating the discriminant validity of our model. This means that the constructs are not only reliable and valid in their own right but also sufficiently distinct from one another, ensuring the integrity of the relationships analyzed in our study.

5.3. Validity of research hypotheses

Finally, we proceeded to estimate the structural model to test the causal relationships between the latent variables. This step involved analyzing the path coefficients, which measure the direct impact of one latent variable on another.

The results in Table 5 revealed the following significant coefficients: a value of 0.42 for the impact of Big Data on the understanding of consumer behavior, a coefficient of 0.37 for the impact of Big Data on consumer satisfaction, and a coefficient of 0.45 for the effect of understanding consumer behavior on their satisfaction.

These coefficients indicate significant and positive relationships, thereby validating our hypotheses that effective use of Big Data enhances the understanding of consumer behaviors and, consequently, their satisfaction. Specifically:

Table 5. Results of hypotheses validity test

Relation	Path Coefficient	p-value
Big Data (BD) -> Understanding consumer behavior (CBC)	0.42	< 0.001
Big Data (BD) -> Consumer satisfaction (SC)	0.37	< 0.001
Understanding consumer behavior (CBC) -> Consumer satisfaction (SC)	0.45	< 0.001

The strong p-values (all less than 0.001) further support the significance of these relationships.

These findings underscore the importance of Big Data as a strategic tool for businesses seeking to optimize the customer experience and strengthen their market position. By leveraging Big Data, companies can gain deeper insights into consumer behaviors, enabling them to tailor their strategies and enhance overall customer satisfaction. This not only reinforces our research hypotheses but also highlights the potential competitive advantage that can be gained through effective data utilization.

Discussion of results

The analysis of our study's results highlights the growing importance of Big Data in understanding consumer behavior and satisfaction. Our data corroborate previous studies and provide an updated perspective on the impact of Big Data in the business realm.

The results show a path coefficient of 0.42 between the use of Big Data and the understanding of consumer behavior, thus validating our hypothesis H1. This relationship aligns with the work of Li el al (2022) who has confirmed that big data provide companies with the necessary analysis tools to understand consumer behavior, in addition to the work of Sarprasatham (2016) And of Qiu el al (2023) who have demonstrated from their side, by their way, that Big Data enhances the understanding of consumer's behaviors including motivations and purchasing behaviors.

The coefficient of 0.37 for the impact of Big Data on consumer satisfaction supports our hypothesis H2. This finding aligns with the research of Lemon and Verhoef (2016), which shows that the personalization of offers, enabled by Big Data analysis, enhances customer satisfaction. The findings are aligned also with the points of Ju, (2022) and Wu, (2023) that they have said that the use of Big data analysis and its algorithms have a significant impact on customer satisfaction.

Finally, the coefficient of 0.45 for the effect of understanding consumer behavior on satisfaction validates our hypothesis H3 reinforcing findings from Rusdian el al, (2024) and Wang el al., (2016) that have highlighted that a deep understanding of consumers' behavior can have a direct impact on their satisfaction.

Overall, our findings affirm the strategic importance of Big Data in today's commercial landscape. Analyzing this data enables companies to enhance their understanding of consumer behaviors, optimize satisfaction, and consequently strengthen their market position. These results offer significant practical implications for businesses seeking to fully exploit the potential of Big Data in their commercial strategies.

Strategic insights and recommendations

The findings of our study underscore the strategic importance of Big Data in enhancing both consumer understanding and satisfaction. Businesses can leverage these insights to develop targeted marketing strategies that align closely with consumer preferences. For example, implementing advanced analytics tools enables companies to segment their customer base more effectively, allowing for personalized marketing campaigns that resonate with specific groups. By utilizing machine learning algorithms, organizations can predict consumer behaviors and trends, anticipating market shifts and adapting their offerings accordingly.

However, while these insights are valuable, it is essential to acknowledge the limitations of the study. The sample size of 300 respondents, although sufficient for preliminary analysis, may not fully represent the diverse consumer landscape, particularly across different demographics or geographic regions. Additionally, the cross-sectional nature of the data limits the ability to draw causal inferences over time. Future research should aim for larger, more diverse samples and consider longitudinal designs to better understand the evolving dynamics of consumer behavior in relation to Big Data.

Looking ahead, future studies should explore the long-term effects of Big Data utilization on consumer satisfaction, possibly through longitudinal research that examines changes over time. Investigating different industries could yield insights into sector-specific applications of Big Data analytics. Furthermore, research could focus on the impact of emerging technologies, such as artificial intelligence and blockchain, on consumer behavior and satisfaction.

This research contributes to the existing literature by validating the relationship between Big Data analytics and consumer behavior understanding, as well as satisfaction. It supports theories related to consumer decision-making and marketing effectiveness, reinforcing the notion that data-driven strategies are essential in contemporary business environments.

The results affirm the critical role of Big Data in shaping consumer insights and enhancing satisfaction. By effectively utilizing data analytics, businesses can not only improve their marketing strategies but also foster stronger relationships with their customers. This alignment between consumer expectations and business offerings is increasingly vital in today's competitive market landscape.

To capitalize on these findings, companies should invest in robust data analytics platforms capable of handling large volumes of diverse data. Training staff to interpret and act on data insights is crucial. Additionally, organizations should prioritize the ethical use of consumer data, ensuring compliance with privacy regulations while building trust with their customer base.

As businesses harness Big Data, ethical considerations must be at the forefront. Companies should ensure transparency in their data collection processes and communicate clearly with consumers about how their data will be used. Adopting ethical guidelines can enhance consumer trust and loyalty, ultimately leading to improved satisfaction outcomes.

5. Conclusion

This study emphasizes the essential role of Big Data in enhancing understanding of consumer behavior and improving customer satisfaction. In an era characterized by rapid digital transformation and an overwhelming amount of data, organizations that effectively leverage this information stand to gain significant competitive advantages. The research demonstrates that Big Data analytics allows businesses to delve deeper into consumer preferences, identify emerging trends, and adjust their marketing strategies accordingly. This adaptability not only leads to a more personalized customer experience but also fosters greater loyalty and satisfaction among consumers.

The results indicate a strong positive correlation between the use of Big Data and improvements in both the understanding of consumer behavior and overall satisfaction. For instance, businesses utilizing advanced analytics and machine learning algorithms can segment their audiences more effectively, leading to targeted marketing efforts that resonate with specific consumer groups. This personalized approach enhances customer experiences and addresses individual needs, which is increasingly vital in a marketplace where consumer expectations are continually evolving.

Despite these promising findings, the study acknowledges several limitations. The sample size of 300 respondents, while sufficient for preliminary analysis, may not fully capture the diverse landscape of consumers, particularly across various demographics and geographic regions. Additionally, the cross-sectional design restricts the ability to draw causal inferences over time. Future research should strive for larger and more varied samples to enhance the generalizability of the findings, and longitudinal studies could provide deeper insights into how consumer behavior and satisfaction evolve in relation to Big Data over time.

Looking ahead, further exploration of the long-term effects of Big Data on consumer satisfaction could yield valuable insights, particularly across different industries. Investigating how emerging technologies, such as artificial intelligence and blockchain, intersect with consumer behavior and satisfaction could also provide a richer understanding of the landscape.

In conclusion, the study affirms that effectively harnessing Big Data is not just a technological trend but a strategic necessity for modern businesses. By employing data analytics to gain insights into consumer preferences and behaviors, organizations can create stronger connections with their customers, ultimately driving growth and success. As businesses continue to adapt to the complexities of the digital marketplace, the insights derived from Big Data will be crucial for maintaining a competitive edge and ensuring sustained customer satisfaction.

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